



58. Robotics in Hazardous Applications

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Robotics researchers have worked hard to realize a long-awaited vision: machines that can eliminate the need for people to work in hazardous environments. Chapter 60 is framed by the vision of disaster response: search and rescue robots carrying people from burning buildings or tunneling through collapsed rock falls to reach trapped miners. In this chapter we review tangible progress towards robots that perform routine work in places too dangerous for humans. Researchers still have many challenges ahead of them but there has been remarkable progress in some areas. Hazardous environments present special challenges for the accomplishment of desired tasks depending on the nature and magnitude of the hazards. Hazards may be present in the form of radiation, toxic contamination, falling objects or potential explosions. Technology that specialized engineering companies can develop and sell without active help from researchers marks the frontier of commercial feasibility. Just inside this border lie teleoperated robots for explosive ordnance disposal (EOD) and for underwater engineering work. Even with the typical tenfold disadvantage in manipulation performance imposed by the limits of today's *telepresence* and teleoperation technology, in terms of human dexterity and speed, robots often can offer a more cost-effective solution. However, most routine applications in hazardous

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environments still lie far beyond the feasibility frontier. Fire fighting, remediating nuclear contamination, reactor decommissioning, tunneling, underwater engineering, underground mining and clearance of landmines and unexploded ordnance still present many unsolved problems.

58.1 Operation in Hazardous Environments: The Need for a Robotics Solution

Routine work in hazardous environments presents many challenges for robotic devices that depend on both the tasks and the hazards. Hazards may be present in the form of temperature extremes, radiation, toxic fumes

and materials, potential explosions, risk of electrocution, the absence of breathable air in space, and the high pressure of underwater environments. When the magnitudes of one or more hazards reach the point

that human exposure would either represent a direct threat to life or unacceptable long-term health consequences, some form of remote operations that separate humans from the hazards must be employed. A long-extant example of such operations is the nuclear industry where telerobotics has become a well-established technique for operations in environments with high levels of nuclear radiation. Many of the technical roots of modern robotics technology can be traced back to nuclear remote handling manipulators and support systems. Remote handling and operations concepts using engineered systems that allow humans to perform hazardous work while staying in a safe environment have evolved since the 1940s. Today, such remotely operated systems are widely used and recently they have become routinely used in explosives disposal, security operations, handling of dangerous biological materials, and routine inspection of industrial systems such as power lines, substations, sewers, piping systems, pressure vessels and many others.

A remote handling system will generally involve subsystems for mobility, manipulation, tooling, sensing, and human-machine interfacing (Fig. 58.1). Nominal operations involve the collective workings of these subsystems to accomplish remote operational goals. Any remote handling system will eventually experience some aspect of off-nominal operation that may be the result of unexpected environmental events or system malfunctions. The fundamental idea is to connect the human operator to the remote environment via a power and signal infrastructure that allows effective operation in the remote environment: mechanized devices and sensor systems that allow the human's perception and action capabilities to be *projected* into the hazardous environment to perform remote operations. The more

realistic this projection, the more natural and effective the human remote control will be.

Because of their inherent complexity and the very nature of remote operations, operator training is a major challenge that requires the use of simulations and cold testing facilities that provide operators with comprehensive and realistic training. Such training will typically encompass all aspects of nominal and anticipated off-nominal operations.

Remote handling systems themselves will eventually experience equipment failures. Remote recovery/maintenance/operation of failed remote systems must be an integral part of their basic design and operational features. Hardware/software features must be provided for the analysis of, recovery from, and correction of problems.

Robotics researchers have worked hard to realize a long-awaited vision: machines that enable people to perform routine work without exposure to hazards. In this chapter we review progress and some of the current and future challenges that lie ahead for researchers.

Technology that specialized engineering companies can develop and sell without active help from researchers marks the frontier of commercial feasibility. Just inside this border lie teleoperated robots for explosive ordnance disposal (EOD) [58.1, 2] and for underwater engineering work. Even with the typical tenfold disadvantage in manipulation performance imposed by the limits of today's *telepresence* and teleoperation technology, compared with human dexterity and speed, robots can often offer a more cost-effective solution. Naturally, if people need to wear protective suits to protect them from hazards, their endurance and dexterity will be restricted.

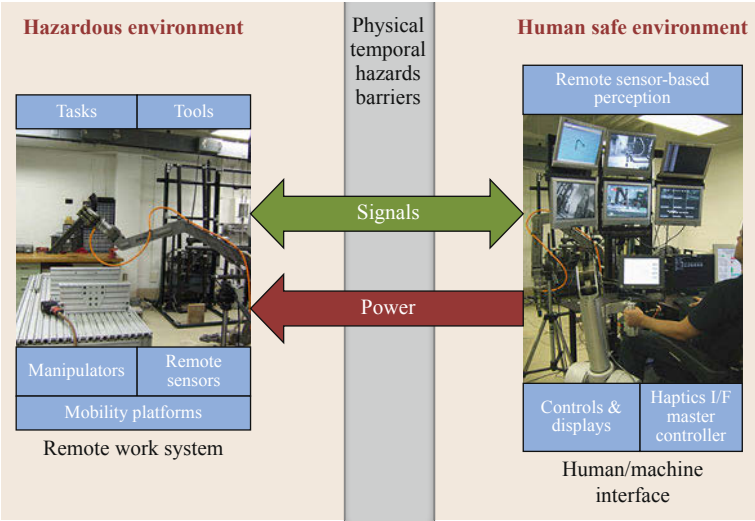


Fig. 58.1 Basic subsystems of a remote handling system

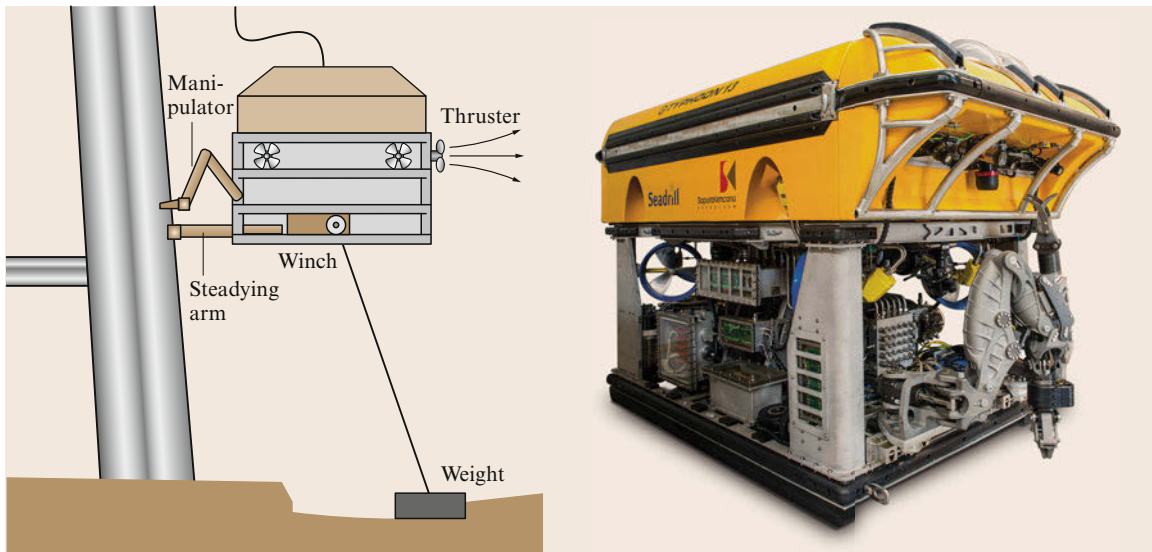


Fig. 58.2 Remotely operated vehicles designed for underwater engineering work, demonstrating an ingeniously simple technical arrangement compared with conventional free-swimming vehicles. (courtesy of Total Marine Technology, Australia)

Ingenuity stimulated by commercial incentives can greatly reduce the operating costs of remotely operated equipment. Figure 58.2 illustrates the elegant simplicity of the NOMAD remotely operated vehicle (ROV) that pulls itself deeper with a simple electric winch. It can be left in place overnight or during rough weather. Free-swimming robots are much more complicated and expensive and have to be hauled out of the water when not under active control.

Limited autonomy or autonomous operation for a restricted time can relieve operator fatigue and allows unmanned aerial vehicles (UAVs, often referred to as drones) to fly extended reconnaissance missions with occasional precision weapon delivery. Such missions would be too hazardous or too politically sensitive for manned aircraft.

Even after the first decade of the 21st century, with 60 years of remote operating experience, most haz-

ardous applications still lie far beyond the frontier of commercial feasibility. Fire fighting, remediating high-level nuclear contamination [58.3], reactor decommissioning, tunneling, underground mining, and most landmine and unexploded ordnance problems still present many research challenges. Most attempts to use first-generation mine rescue robots reported in the press in 2000 and 2001 have merely created distractions for the people who regularly have to risk their lives saving their trapped colleagues (e.g., the Australian Numbat robot [58.4]). The Fukushima Daiichi nuclear reactor disaster triggered by the March 2011 tsunami that devastated parts of Japan serves as a reality check on our capacity to use robots effectively for hazardous tasks. Beyond the carefully engineered environments that characterize the nuclear material handling industry, the disappointing performance of several robots has demonstrated just how far we still have to go.

58.2 Applications

Potential applications of robotic systems in hazardous environments encompass an extremely wide spectrum, limited only by human imagination. The solutions for these different environments are equally diverse. In general such applications involve unique challenges associated with the uncertainty and unstructured nature of the associated tasks. In this discussion, two application areas that are very different have been selected

to give the reader a deeper sense of technology evolution, accomplishments, and remaining challenges. The first application we will discuss is landmine eradication, sometimes referred to as demining, a current application domain with humanitarian importance and extremely difficult and hazardous outdoor conditions. The second application area is hazardous nuclear and biological material handling, a decades-old industry

that has strongly influenced many aspects of robot manipulation and mobility research and development. We conclude this section with a brief discussion on the lessons learned from the Fukushima Daiichi disaster, lessons that help to strengthen our argument that we are still at a very early stage of development in robotics for routine operations in hazardous environments.

58.2.1 Eradicating Landmines

Efforts to construct a practical robotic device to help with landmine clearance have met with only limited success. While remote control technology has enabled some existing machines and vehicles to be used in hazardous situations, we are still a long way from achieving reliable robotic mine clearance. It is instructive to understand why many expectations turned out to be hopelessly optimistic.

Landmines, a simple type of victim-activated explosive device, were used extensively in Europe and North Africa during the Second World War between 1939 and 1945. Extensive clearance operations in 1945 and 1946 removed nearly all of the landmines then in use [58.5, part 1, pp. 15–25].

Landmines were used extensively in subsequent decades. Along with antipersonnel cluster bombs, they caused extensive civilian and military casualties in Vietnam and Cambodia from the 1960s onwards. However, it was not until their widespread use in Afghanistan,

Angola, Cambodia, and several other countries in the 1980s that they were recognized as a major humanitarian problem. Landmines blocked aid efforts needed to rebuild communities following civil conflicts.

The Red Cross and the International Campaign to Ban Landmines (ICBL) successfully promoted a ban on the use of landmines that came into effect in 1997 as the Ottawa Treaty. The knowledge that thousands of children were losing their legs, even their lives, motivated hundreds of researchers to develop new technologies to help eliminate this threat. By 2000 ICBL estimated that over 80 countries were affected by landmines and other explosive remnants of war such as cluster bombs. Although several countries that have not signed the Ottawa Treaty still have extensive stocks of landmines, the treaty has been effective in restricting the use of landmines more through peer pressure. A few countries and several non-state actors continue to deploy landmines. However, other explosive remnants of war such as cluster bombs and other munitions have become, yet again, an increasing problem in Iraq, Afghanistan, Libya and Syria.

There are several basic types of landmines and unexploded ordnance (UXO) that continue to cause problems in many countries.

Antipersonnel (AP) blast mines, made predominantly of plastic with small metal firing pins and detonator cases, typically contain between 20 and 100 g of explosive (Fig. 58.3). These mines only cause extensive injuries when they detonate within a few centimetres of a person. Typically they lie buried just below the ground surface and are activated when the victim steps on top of the mine. Shattered fragments of bone pass through the flesh of the leg at high velocity. If the victim survives long enough to reach hospital, amputation above or below the knee usually saves his or her life but the victim will need prosthetic legs, replaced at regular intervals.

Antipersonnel fragmentation mines contain similar quantities of explosive with a thick metal case that breaks into high-velocity fragments when the mine explodes just above the ground surface. Older fragmentation mines were mounted on posts; some varieties lie buried but jump into the air when activated and explode at waist height, killing or seriously wounding victims up to 200 m away. These mines are much easier to detect so they are often protected by nearby antipersonnel blast mines to deter theft.

Anti-vehicle (AV) or anti-tank mines (ATs), made predominantly of plastic with small metal firing pins and detonator cases, are large versions of the AP blast mine and typically contain 5–10 kg of explosive. Some have a thick metal plate on top that can penetrate 50 cm of armor plate on the underside of a tank. These mines cause significant damage even to mine-resistant vehi-

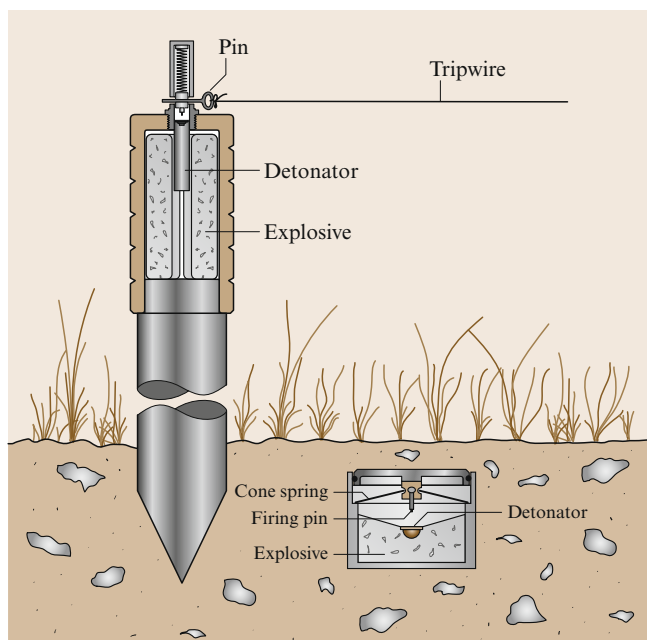


Fig. 58.3 Antipersonnel fragmentation mine (left) and buried blast mine (right)

cles which have blast-resistant hulls, offset wheels, and additional protection for occupants.

Air-dispersed munitions such as cluster bombs (CBs) were not intended to be victim-activated. Several hundred are released at one time from a single canister and they are designed to explode on impact with the ground. Typically between 5 and 25% fail to explode immediately and lie in a partially triggered state either on or just below the ground surface. Some will detonate in response to electromagnetic fields from metal detectors, and others will detonate with the slightest movement. Most explode like powerful fragmentation mines with a lethal radius of up to 200 m.

Improvised explosive devices (IEDs), often in the form of roadside bombs, are increasingly used by insurgent groups fighting organized military forces (asymmetric warfare). They are often made from large UXOs fitted with remote controlled detonators [👁️ VIDEO 572]. Ironically the UXO is often unintentionally donated by the same organized military forces who become the targets of these devices. IED detection and clearance has become one of the highest priorities for military robotics research.

Evolution of Landmine Clearance Techniques

Removing landmines is usually both laborious and hazardous. It is important to distinguish between humanitarian mine clearance and military mine clearance methods (sometimes called *breeching*). Military mine clearance has to work fast, in all conditions (even under fire), and therefore it is unrealistic to aim for 100% clearance. In humanitarian operations there is less time pressure and work can be suspended in unfavorable conditions, and the aim is 100% clearance. Since the 1990s, the expectation in industrialized countries of low casualties from military operations often demands very high clearance standards even for urgent military operations.

Humanitarian mine clearance typically starts years, perhaps decades, after the mines were laid. The mines lie buried or hidden from view. They deter people from entering the land so vegetation often grows thickly (Fig. 58.4). Drainage systems rapidly become clogged, denying access in wet conditions.

The traditional *manual* method for removing landmines has been to use a metal detector to locate metal fragments close to the ground surface and then to carefully check each metal fragment to see if it is associated with a mine or explosive device [👁️ VIDEO 571]. Any tripwires and vegetation have to be removed, with great care, before a metal detector can be used. In many areas deminers have to investigate hundreds or thousands of metal fragments for every mine found. Manual mine clearance also requires careful organization and



Fig. 58.4 Typical ruined house overgrown by vegetation in a village in northern Croatia, possibly containing mines or booby traps. The entire village population was forced to leave in 1991 and the houses were looted and intentionally severely damaged. Vegetation problems like this must be taken into account in considering practical mine and UXO clearance devices. August 1999 (courtesy of J. Trevelyan)

marking of the ground to ensure safety and thorough clearance. Currently it is still the method that guarantees the lowest risk of residual mine contamination but it is expensive, typically costing US\$ 1–5 /m².

Armored mine clearance machines using hammers mounted on the end of rapidly spinning chains (flails) first appeared in the 1940s but have not been able to neutralize mines with sufficient reliability for most humanitarian applications [58.6].

In the late 1990s commercial mine clearance organizations operating in thick vegetation in Bosnia Herzegovina and Croatia realized that flails spinning just above the ground could rapidly remove vegetation and trip wires to prepare the ground for manual clearance, often assisted by mine detection dogs. Clearance costs have been reduced by up to 80% (particularly in thick vegetation) using different combinations of machines, detection dogs, and manual clearance.

Ground milling machines use metal drums studded with hard cutters that shred buried objects. They require more power than flails but can operate with greater levels of reliability (Fig. 58.5). Both flails and ground milling machines have been extensively used in Croatia to recover large areas of formerly productive agricultural land. Both kinds of machines can withstand a limited number of AT and moderate-size UXO explosions before main bearings and other components need to be replaced [👁️ VIDEO 574, 👁️ VIDEO 575, 👁️ VIDEO 576, 👁️ VIDEO 577]. Several of these machines have remote operation capabilities (Fig. 58.6).

Naturally, machines operate best on flat or gently sloping ground, which is also the land that is most valuable for agriculture and human habitation. Thick forest



Fig. 58.5 Flail machine using hammers on the ends of spinning chains to clear vegetation and tripwires. This machine will also detonate a proportion of buried mines (*inset*) (courtesy of Scanjack AB, Sweden)



Fig. 58.6 Bozena teleoperated demining vehicle (courtesy of Way Industry, Slovakia)  **VIDEO 574**

and mountainous terrain still requires traditional manual clearance and, in most countries, will not be cleared of mines for a long time, if ever.

Mechanized clearance methods continue to evolve with improvements to machines and techniques. Machines can be used for survey, risk assessment, and risk reduction tasks to help determine the need for more expensive manual clearance methods. Mine action programs are gradually shifting from an emphasis on total clearance in the 1990s to one of progressive prioritized risk reduction involving a series of measures including high-security fences, mechanized survey and risk reduction methods, and selective manual clearance [58.5, part 4]. Protective measures applied to agricultural machinery offer cheaper alternatives in low-AT-risk areas [58.7].

Evolution of Demining Research Priorities

Technological development in landmine clearance from within the demining community has mainly been driven by the search for improved productivity. Many of the comments in this section are based on numerous discussions with experienced demining personnel who have tried new technologies in the field. References have been cited where further detailed written information is available.

In the mid-1990s there was the expectation that, with sufficient research, advanced technology detectors could replace eddy-current metal detector technology that had been in use since the 1940s. Metal detectors also react to metal fragments in the ground. A detector that could confirm the presence of explosive, it was thought, would save having to investigate all these false alarms. The most promising line of research seemed to be data fusion: combining signals from a metal detector, ground-penetrating radar, infrared detectors, thermal neutron detectors, and even acoustic detectors. Astute observers at research conferences have pointed out that these signals are often well correlated, even in the presence of false alarms: producing a reliable detector was going to be hard work. Their forecasts turned out to be very accurate. Only one such detector is currently in operation: the handheld standoff mine detection system ([HSTAMIDS](#)) detector used by US military forces in Afghanistan employs a combination of ground-penetrating radar and eddy-current metal detection. Little information on its effectiveness has been released and no independent trials have been reported.

Experienced research groups report that ground-penetrating radar requires accurate alignment of the detector with the ground surface (to eliminate ground surface returns) and also with the target center point to enable the target to be characterized reliably. If the principal metal component of the landmine coincides with its geometric center, a common feature of minimum metal mines, the metal detector can be used for alignment. However this is not always the case and one cannot guarantee the absence of other metal fragments near the mine. Ground-penetrating radar provides confusing returns in very dry or very wet conditions and is also susceptible to false alarm indications from underground discontinuities such as stones, sticks, animal burrows etc. Publishers mostly downplay these difficulties and prefer only to report positive results, not false negatives. These issues only emerge from discussions with developers who have seriously evaluated technology in field conditions.

The major performance improvements in sensing have been obtained by compensating eddy-current metal detectors for soil magnetization, enabling them to work in a much wider range of soil conditions. Improvements in sensitivity can help with minimum metal mines but can also result in a large number of false alarms from smaller metal fragments. Metal detector arrays have been fitted to vehicles to speed up clearance of paved areas and roads [58.8].

By the late 1990s slow progress with sensors had become more apparent and research priorities after 2000 gradually turned to mine detection dogs and large demining machines.

The Afghanistan Mine Action Center (MACA) started using mine detection dogs around 1993 but it was not until 1998 that this program was running effectively. There were several difficulties. The first challenge was that close association between humans and dogs was socially unacceptable in Afghanistan. The second challenge was to devise ways to use dogs and manual mine clearance in an effective combination providing reliable clearance with high productivity. This was much the greater challenge, but by 1998 the cost of clearance using dogs was around one-third the cost of manual clearance. It was then that the problems started to appear: the occasional missed mine that could not be explained by lack of organization or failure to follow procedures. At the same time, carefully controlled trials of mine detection dogs in Bosnia had returned highly variable results. On several occasions dogs had walked past blocks of trinitrotoluene (TNT) lying almost visible in the ground. Yet, at the same time, a number of commercial demining agencies were routinely declaring land free of mines using similar dogs. In late 1999

the Bosnian Mine Action Center ran a carefully controlled test in which around 80% of the dogs failed to achieve the required performance standard. The results were hotly contested at the time and the international community organized a systematic trial of mine detection dogs through the Geneva International Centre for Humanitarian Demining (GICHD).

By 2001 it was apparent that there had been little scientific research on the fundamental physiological mechanisms that enable dogs to locate sources of explosive vapor. Dogs had been able to find mines using explosives (such as high melting point explosives like HMX) with vapor pressure far below measurable detection thresholds. The mechanism by which TNT vapor and its breakdown products reach the ground surface was the subject of considerable scientific debate. By 2003 a systematic trial in Afghanistan, scientific studies at SANDIA Laboratories in the USA and in Scandinavia, explosive trace detection studies with dogs at Auburn University, and several other investigations provided some insight into this problem for the first time [58.9]. However, the precise physiological mechanisms for canine explosive detection remain unclear, especially for lower-vapor-pressure explosives. We still do not know for sure whether dogs are reacting to vapor, minute particles of explosive suspended in the air, biochemical breakdown products, or a combination.

In 2003 a US company, NOMADICS, demonstrated the FIDO detector, the first that could reliably measure the presence of TNT vapor with greater sensitivity than a highly trained dog. However field trials showed that TNT vapor could be detected everywhere in a mine contaminated area. An explosive vapor sensor was just the beginning of the story and warns of a complex cognitive task ahead in using the patterns of variation to localize targets.

By 2004 the international community realized that the early confidence in a breakthrough resulting from advanced sensor technology, demining machinery, and mine detection dogs had been misplaced. GICHD commissioned a detailed study of manual demining to see whether productivity improvements could be made. A systematic series of trials were conducted in Africa to determine the effectiveness of several innovations such as magnets and rakes. The final report, issued in 2005, revealed that greatly improved productivity was possible but would depend more on improving contracting arrangements, management, and training than technology.

The New York attacks in September 2001 fundamentally changed research priorities. Removing unexploded ordnance, particularly cluster bombs, became the top priority for the next 12 months in Afghanistan

(Fig. 58.7). Since then the deteriorating security and political situation in Afghanistan has focused mine clearance agencies more on maintaining security for their own workforce than trying to improve productivity and safety.

Resistance to the US and international occupation of Iraq and the easy availability of explosives both from former Iraqi armed forces and unexploded ordnance from US military operations led to the proliferation of improvised explosive devices (IED) to attack organized military forces and police. These have now become the main threat and the focus for much of the funding, and operational and research expertise formerly available to support mine clearance operations. This development has also placed ordnance disposal teams at the front line for the first time, rather than working in well-protected secure areas. Iraqi insurgent groups attack ordnance disposal teams both because they are attempting to disarm some of the insurgents' most effective weapons and also because they remove the main sources of explosives available to insurgent groups.

Improvised explosive devices, when detected, are often investigated and neutralized using remotely operated robots. While there are non-destructive methods to neutralize IEDs, the fastest method usually involves placing a small shaped charge device close to, and accurately aligned with the device. Operational details remain confidential to reduce the risk that IEDs will be modified to defeat current neutralization methods.

Paradoxically it is this development that has enabled robotics to make a greater contribution to the problem



Fig. 58.7 Unexploded BLU-97 cluster bombs in Afghanistan early in 2002. Two of the small yellow canisters with parachutes still attached lie visible in the foreground. Others lie in the houses in the distance. Some may lie up to 40 cm below the ground surface. Some can detonate when a metal detector or mobile phone is used nearby. These devices have a kill radius of 200 m and can sometimes be set off by a strong gust of wind. They readily attract the curiosity of children (courtesy of G. Zahachewsky and N. Spencer)

by through improvements in remote manipulation technology. These improvements come more in the form of low-cost commercial off-the-shelf components (mobile platform, motors, TV cameras etc.) than from fundamental research advances. Improvements are still being made: improved remote manipulation, blast survivability, operator interface improvements, and mobility improvements have all contributed significantly to performance and reduced operating costs.

Advances in Demining Robotics Research

In a brief survey it is not possible to mention every contribution. We have attempted to provide a sample of research reports that illustrate the main achievements and we present brief technical discussions on mobility and manipulation dexterity.

Teleoperation remains the only robotics technology that has been used in practical application in field conditions [58.10–12], even with devices such as iRobot and machines such as MineWolf. Robotics research has not yet been able to make a significant contribution to mine and unexploded clearance work. However, the problems posed by landmine clearance have stimulated new research results that could have other applications.

Robotics researchers started their efforts in the early 1990s, for example, Havlik and Trevelyan independently proposed suspended cable robots to work in minefields [58.13]. However, both have later argued in favor of alternative solutions [58.10, 14].

Nicoud [58.15] wrote one of the first surveys exploring the possibility of using robotics technology for landmine clearance. Developments in robotics research since the mid 1990s have been motivated both by a genuine desire to help combat a serious humanitarian issue and also by a desire to find a justification for more fundamental research. However, most researchers still have not learned lessons from the field such as the need to remove vegetation and the variety of situations in which deminers find themselves [58.16].

One of the most prolific research areas justified in part by humanitarian demining problems has been path planning for autonomous agents [58.17]. Probabilistic approaches were explored by [58.18]. Some researchers have proposed multiple robot solutions, even *swarms* of robots [58.19] and so-called *immune systems* [58.20]. Autonomous search and mapping algorithms have also been explored [58.21], including even three-dimensional (3-D) search techniques for locating underground chemical sources [58.22].

Landmine clearance has also stimulated developments in autonomous robot vehicles, with many examples in the literature [58.23]. Tracked vehicles have been proposed for working in rubble and built environments [58.24]. Walking vehicles have been proposed,

particularly for difficult terrain in countries like Bosnia and Afghanistan [58.25] even to the extent of examining how damaged robots with missing legs could extricate themselves from a mined area [58.26].

The desire to keep human operators away from the risk of handling unexploded ordnance has stimulated research on artificial hands and telemanipulation [58.27]. Purely mechanical devices have also been explored [58.28]. Several researchers have provided detailed results of tests with manipulators mounted on autonomous vehicles [58.29] (Fig. 58.8).

Robotics solutions have also been proposed partly to overcome the limitations of handheld sensors such as ground-penetrating radar. A robot manipulator can control the motion of the sensor so much more precisely, opening the possibility of synthetic aperture techniques for both metal detection and radar [58.30].

Military research agencies in the United States, Australia, Britain, and Canada devoted large research budgets to the problem of road clearance since AT mines and IEDs accounted for a large proportion of military casualties in Somalia, Bosnia, Iraq and Afghanistan. Insurgent forces had demonstrated that they could bring organized military forces to a complete standstill overnight simply by laying anti-vehicle mines in a few road potholes. With most roads in poor condition there was no easy way to detect that the mines had been laid. Insurgents would typically use mines to stop leading vehicles in a convoy in order to increase the effectiveness of an ambush.

Most research teams proposed one or more vehicles carrying multiple sensors including ground-penetrating radar, metal detector arrays, passive and active infrared, and even some acoustic arrays. Some sensor arrangements were designed to look forward sufficiently far to allow the carrier vehicle to stop before reaching a mine. Others were to be carried by lightweight remotely controlled lead vehicles. Military planners calculated that search speeds of ≈ 30 km/h would be required to be able to check roads daily in time for supply convoys to use the roads in daylight hours. Many different arrangements have been reported [58.31]. Other teams proposed teleoperated devices for landmine and explosive ordnance detection and neutralization but few anticipated the requirement to operate under armed attack. Typical requirements envisaged secure rear area mine clearance in combat situations and peace-keeping on roads and tracks [58.32] or force protection roles [58.33]. Most of these efforts were initiated in the late 1990s but by 2005 it had become apparent to military planners that vehicle protection rather than mine detection was a more practical solution. Much of today's vehicle protection technology originated in southern Africa with further development in Australia,



Fig. 58.8 Gryphon experimental robot on trial in Cambodia (after [58.29] courtesy of S. Hirose)

the UK, and other countries, stimulated in part by South African expatriates.

One way to reduce the distance between researchers and field problems, at least in terms of geographic distance, has been to promote research in landmine-affected countries such as Sri Lanka and Colombia [58.34]. However this is not easy. Most countries affected by landmines have been disrupted by social conflict and destabilization that led to the military conflicts in which landmines were used. This makes it difficult for local people to create sufficient economic and physical security for researchers to pursue their work.

Future Prospects for Robotic Demining

What are the challenges for robotics researchers working on landmine clearance and other hazardous applications in the future?

We need further advances in mechatronics design, sensing, and accurate understanding of the problems to be solved using robots.

The best starting point for research is to witness people undertaking hazardous work in several different situations. Nuclear accidents, mine disasters, and burning buildings are usually off-limits to researchers. However, mine clearance operations are readily accessible in many countries. Though many researchers think a visit would be far too hazardous, there is no better way to appreciate the practical difficulties involved. Photographs taken at mine clearance operations are available to provide researchers with a web site for reference purposes, partly in answer to this need to understand the practical realities [58.35].

One of the main motivations for robotics researchers has been the perception that mine clearance is a hazardous occupation and that it would be more preferable for robots to be exposed to minefield risks

than human beings [58.36]. While mine clearance is certainly a hazardous occupation it is not necessarily dangerous. Accident records show that mine clearance in Afghanistan in 1998 resulted in about half the rate of injury of the United States forestry industry and about one third the rate of injury for the United States building construction industry per 100 000 working hours. Mine clearance agencies use advanced techniques to improve safety when possible [58.37]. In terms of deaths, demining is considerably less hazardous than mining, construction of building foundations, and especially offshore drilling rigs [58.38, pp. 11–14].

Another motivation for research is to reduce deaths and injuries among local people who have to live with the daily threat of landmines and unexploded ordnance. Again, there are misperceptions of risk. The incidence of death and injury from mine explosions is often very small compared with disease, for example. The main priorities for local people tend to be improvements for water and food supplies, education, sanitation and physical security: landmine clearance is usually a much lower priority and it is often hard to justify significant local resources.

It is also important that robotics researchers intending to contribute to the solution of this problem understand the relatively small size of humanitarian demining operations, which have been funded from a combined international humanitarian aid budget of approximately US\$ 400 million. These programs spend an estimated \$ 20 million annually on all equipment needs. The market for specialized humanitarian demining detectors is therefore very small and manufacturers cannot afford research and development specifically to support humanitarian demining solutions [58.39]. Adapting technology developed for other purposes, such as military equipment or civil engineering construction machinery, is more likely to be feasible.

From 1990 to 2014 there were significant improvement in mine clearance techniques but overall progress is still slow and robotics may well provide the final solution in the long term. There are still opportunities to develop robotic techniques that could ultimately provide the only cost-effective method for finally eliminating this menace.

58.2.2 Hazardous Materials Handling and Operations

The oldest application of robotics-related technology to hazardous environments is various aspects of remote nuclear operations dating back to the beginning of serious work on atomic physics in the early 1940s. This section discusses hazardous materials and operations in the context of nuclear applications and some extrap-

olations to other domains. These applications run the spectrum from low- to high-fidelity manipulation and multiple mobility modes.

In the 1940s, research in atomic physics led to a new era in remote handling as scientists sought to explore the nature of materials involving ionizing radiation. As experiments became more complex, mechanical manipulator systems were created which allowed operators to perform increasingly complex tasks safely behind thick biological shielding [VIDEO 586](#), [VIDEO 587](#), [VIDEO 588](#), [VIDEO 590](#). These mechanical systems then evolved into electrical systems that allowed larger work volumes to be considered. Incredible engineering achievement occurred in a 15 year period within the Remote Control Division of the Argonne National Laboratory. Even though this era represented tremendous technical achievement, it went further in illustrating the intrinsic complexity of remote operations. The equivalent work performance achieved with sophisticated teleoperated remote systems is poor in comparison to what human workers can achieve with direct contact operations and common tools. Typically, this form of teleoperation (i.e., manual control over a physical distance or barrier) is ten to hundreds of times slower than the equivalent operations performed directly by a human. Remote operations are extremely expensive and time consuming and have been the continual target of engineering improvements over the years.

Many research and development efforts have focused on different avenues for improving the work efficiency of teleoperated remote operations [VIDEO 589](#). These efforts have included the development of better manipulators, control stations, control algorithms, etc., all intended to enhance reliability and maintainability. In the late 1960s and early 1970s, as digital electronics became more cost effective, interest began to emerge in the integration of automation with teleoperation as a scheme to effectively increase remote operations work efficiency. It was around this time that industrial robot concepts were also introduced. Combining selective automation of specific subtasks with traditional teleoperation offers the potential to reduce labor requirements and to improve the quality of repetitive task executions. This integration of automation with teleoperation became the foundation of what is now termed *telerobotics*. From the 1970s until today, telerobotics has been an active area of research and development in many different domains that include nuclear, space, and military applications. Unlike manufacturing automation, remote operations in hazardous and unstructured work task environments necessitate human-in-the-loop control, or teleoperation, at least as a backup, to assure safe operations. Teleoperation related to hazardous materials

and operations, in the most general sense, involve mobility and the use of manipulators to handle objects and tools to accomplish useful work in predominantly unstructured and uncertain environments.

Over the years, there have been numerous papers, books, and reports written concerning technical challenges, issues, and solutions. Readers will find *Vertut* and *Coiffet* [58.40] and *Slutski* [58.41] provide comprehensive and general information about manipulators and systems.  **VIDEO 590**. The performance and design of effective teleoperated systems are strong functions of human factors and *Kraiss* [58.42] and *Johnsen* and *Corliss* [58.43] provide good discussions of key principles. Finally, control system hierarchies and structures are explained in depth by *Sheridan* [58.44]. A final emphasis to all readers would be to fully explore the annals of the American Nuclear Society's Remote Systems Division, later renamed Robotics and Remote Systems Division (**RRSD**). Over the decades, this division hosted numerous topical meetings and workshops on all aspects of remote operations. A starting point is <http://rrsd.ans.org/pages/topicals.html>.

Past Perspectives

Initially, science and experiments involving dangerous radiation levels were accomplished through the innovative use of shielding walls, long-handled tools, and mirrors. As the tasks became more difficult, mechanical arms that could do a better job in emulating human motions were pursued. These ideas represented schemes whereby human sensing and handling capabilities could be more completely *projected* into the remote work environment [58.45]. One of the first challenges that the Argonne group tackled was the development of the mechanical master–slave manipulator. The basic concept was to create a mechanism that would have a master controller side where an operator could provide position and orientation commands to a slave-side mechanism/linkage system that would *replicate* motions and forces in the remote work area. It was felt that force reflection to and from the master and slave systems was essential for the operator's sensory awareness of the task execution. Experimentation has repeatedly verified the significance of both kinesthetic and tactile feedback in performing more complicated tasks [58.46].

Today, master–slave manipulator (**MSMs**) are used around the world in nuclear, biological, and other types of hazardous remote experimentation and operations. (They have also become increasingly used for so-called robotic surgery.) The remote work efficiency of a dual-arm **MSM** with shielded-window viewing is around 5–10 times slower than equivalent direct human contact operations. Because the master and slave sections of

MSM's are mechanically coupled through the metal-tape drive transmission, the physical separation that can exist between the safe operating area and the hazardous remote work area is limited to a maximum of ≈ 10 m. Because of this characteristic and their kinematics, **MSMs** are restrictive in many applications and often have constrained the physical design of remote cells. The Argonne group and others recognized that it would be much better to have the equivalent of a fly-by-wire **MSM** in which the physical separation of the master and slave could be larger. This need led to the development of electrical master–slave manipulators (**EMSs**) that are commonly called electrical servomanipulators [58.47, 48]. Research and Development on the **EMS** began in the late 1940s and continued into the early 1950s.

The Argonne group was at that time limited by the available electrical control technology. Nonetheless, they made noteworthy progress toward integrated systems, as depicted in Fig. 58.9. The prototype system shown is a dual-arm anthropomorphic system with head-aiming remote television viewing and bilateral force reflection. After the Argonne Remote Control Division was disbanded, limited research and development occurred until the 1970s when commercial nuclear power growth was driving a number of research programs in the US, West Germany, France, and Japan. During this time, the programs in the US and France were focused on electrical servomanipulator systems which incorporated emerging microprocessor technology. The Central Research Laboratories model M2 system, shown in Fig. 58.10, was jointly developed with the Oak Ridge National Laboratory and was the first force reflecting servomanipulator system to use distributed digital electronics to implement position–position force reflection with multiplexed serial communications between the master and slave. The

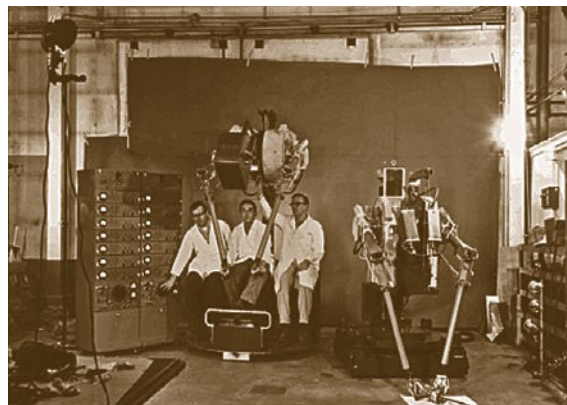


Fig. 58.9 An integrated electrical master–slave manipulator system (courtesy of Oak Ridge National Laboratory)

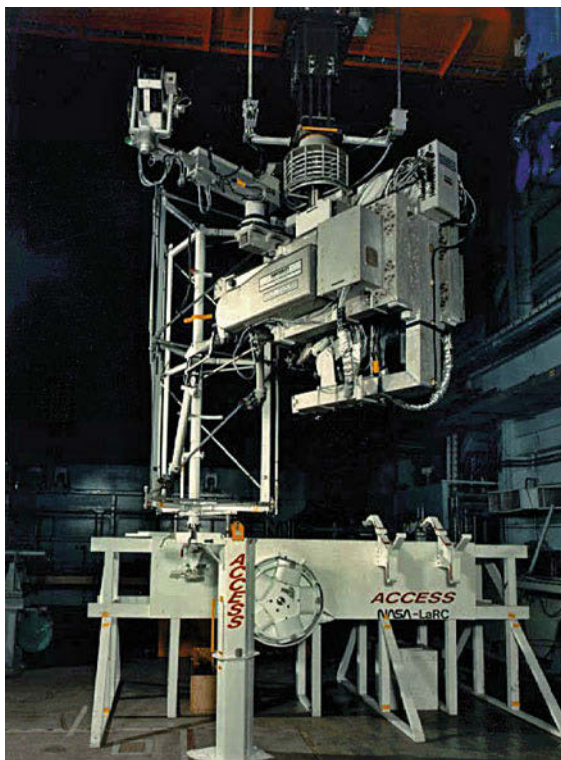


Fig. 58.10 CRL Model M2 manipulator system performing space truss assembly (courtesy of Oak Ridge National Laboratory)

model M2 system was used over the years to explore remote operations for military, space, and nuclear applications.

The development of the advanced servomanipulator (ASM) followed the M2 in an effort to improve the remote maintainability of the manipulators themselves. This work was one of the earliest modular robotics efforts. The motivation for this work was to reduce maintenance technician radiation exposure and to increase the overall availability of the remote maintenance system. The ASM was designed from the beginning to provide a foundation for telerobotics in addition to effective teleoperation [58.49] (Fig. 58.11).

At the time of the M2 and ASM developments, Jean Vertut and his colleagues in the Commissariat à l'Énergie Atomique (CEA) focused their research on the development of telerobotic functionality for their MA-23 electrical servomanipulator systems. This research appears to include some of the earliest experimental demonstrations of telerobotic functions [58.40]. They called their concept computer-assisted teleoperation and it included both operator assists and robotic teach/playback functions. Operator assists included software jigs and fixtures designed for the improve-

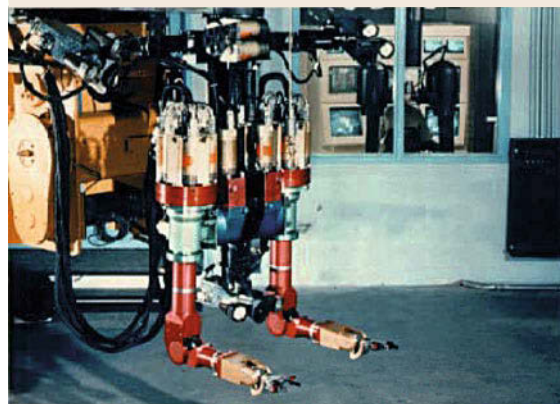


Fig. 58.11 Advanced servomanipulator system (courtesy of Oak Ridge National Laboratory)

ment of the remote operation of tools such as saws, drills, etc.

In the 1980s and 1990s as nuclear power activities began to decline, nuclear remote operations technology was migrated into other areas such as space and the military. Nuclear remote operations experience with teleoperation influenced the Space Shuttle remote manipulator system and the short-lived Flight Telerobotic Servicer program.

In the mid 1990s, substantial interest developed in the application of remote handling systems to deal with problems in hazardous site/facility remediation, such as those associated with defunct nuclear facilities in the US and in Eastern Europe. The intrinsic complexity of remote clean up operations continues to drive research and development in all aspects of teleoperated and telerobotic systems. Challenges and accomplishments in this application area are discussed in the next section.

Hazardous Site Clean Up Applications

Robotic and remote systems have been used in assessing the status of sites contaminated with hazardous

materials. These surveys are essential in planning and executing subsequent clean up operations. Such systems have been used most extensively in nuclear waste sites around the world because remote techniques are more common in many nuclear operations. There has been some use of robotic survey systems in chemical and biological hazard situations as well.

Survey Systems. Numerous robotic survey systems have been developed and used. The basic idea is to integrate a sensor suite, appropriate for the contaminants of interest, with a suitable mobile platform that incorporates remote and/or autonomous driving functions and requisite navigation and control functions. The desired output of the survey process is a *precise* map of contaminant locations and concentrations. Such systems have been developed for both outside and inside operations.

It was common practice in many industries for a number of decades to bury hazardous wastes in earthen trenches in isolated burial sites [VIDEO 591](#), [VIDEO 592](#), [VIDEO 593](#). Usually, useful records of what materials were buried at what locations either did not exist or were not accurate. In fact, the general conditions of such buried waste sites are often unknown to the extent that human entrance is not allowed. As a result, the first step toward remediation is to quantitatively assess the physical and hazard conditions of the site. The mobile robot shown in Fig. 58.12 is an example of a survey system used to evaluate nuclear waste buried waste sites. The robot's location is monitored with Global Positioning System (GPS). The suite of sensors includes eddy-current probes and ground-penetrating radar that reveal density contours, radiation detectors, and gas emissions monitors. This system was an initial prototype that could be operated from a remote driving station or operated in autonomous programmed trajectory mode. The system was controlled using a radio communication link. Its unique feature is that it was designed with minimal use of ferromagnetic materials to minimize interference with the magnetic subsurface sensors.

The mobile characterization system shown in Fig. 58.13 is a similar concept for radiation survey of floored areas. This particular system uses a Cyberbot commercial mobile platform, triangulation of optical fiducial markers for localization, and operates primarily in a full autonomous mode. The objective in this application is to reduce labor costs and eliminate error-prone tedious human operations.

Excavation Systems. The actual remediation of buried wastes ultimately leads to digging and object-handling type operations. Various types of systems in-

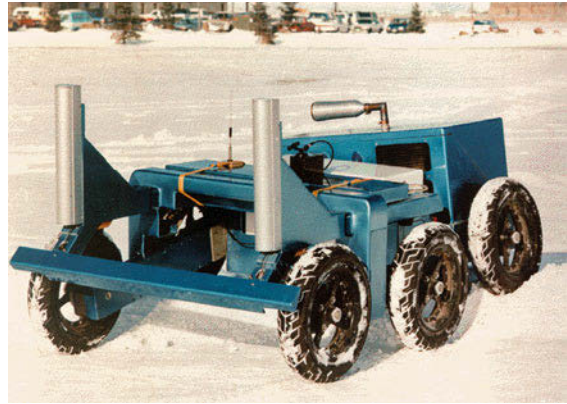


Fig. 58.12 Prototype buried waste survey robot (courtesy of Los Alamos National Laboratory)



Fig. 58.13 Mobile characterization system (courtesy of Oak Ridge National Laboratory)

volving integrated mobility and manipulation-like functions have been developed. One of the most popular and low-cost approaches has been to retrofit conventional excavation equipment with sensor and actuators that allow remote and robotics operations. Such systems have been used in explosive ordnance disposal also. The system shown in Fig. 58.14 is called the teleoperated small emplacement excavator (TSEE) and is a prototype remotely operable backhoe for such applications. The unit included a multi-camera remote viewing system that is the primary basis for teleoperation. Radio and tether communications connections are used to allow the human operators to be displaced up to several kilometers from the hazardous operations.

Deactivation and Decommissioning Systems. In recent years, one of the most complex forms of hazardous operations is the deactivation and decommissioning (D&D) of defunct facilities where nuclear radiation or toxicity hazards preclude human presence.



Fig. 58.14 Remotely operated excavator (courtesy of Oak Ridge National Laboratory)



D&D can be thought of as remote demolition for the most part. Some operations are crude such as knocking down building structures and debris removal. Other operations may involve careful disassembly of equipment and devices, size reduction and packaging of handling/storage. These operations are essentially the inverse of remote maintenance and require the dexterous use of tools and handling of objects. Tools include saws, hydraulic shears, impact wrenches, and the like. Planning and situational awareness are very important in demolition-type operations because the physical layout and stability of the basic environment is changing during the process. Effective remote viewing (adjustable multiview capabilities) and acoustic sensing are essential. Audio feedback from the remote environment provides the human operator with the ability to monitor the normalcy of tooling operations such as sawing. D&D applications require manipulators that are both dexterous and massive. Experience has shown that payload capacities on the order of 100 kg are needed to deal with debris handling, typically with manipulators of the type shown in Fig. 58.15. Figure 58.16 is a frame view from one of the remote viewing cameras used to operate a similar system that was used to D&D an old experimental nuclear reactor. A manipulator is being used to teleoperate a conventional circular saw to segment a large-diameter aluminum tank. This operator view of the remote environment provides a realistic perception of the task environment lighting conditions and complexity.

In recent years, numerous remote manipulation systems for nuclear applications have been developed around industrial robots. These systems are augmented with sensors and master controller arrangements to facilitate teleoperation. This approach offers significant cost savings and the level of teleoperation performance achievable in complex task environments has steadily increased [58.50–54].



Fig. 58.15 Dual-arm D&D manipulator system (courtesy of Oak Ridge National Laboratory)

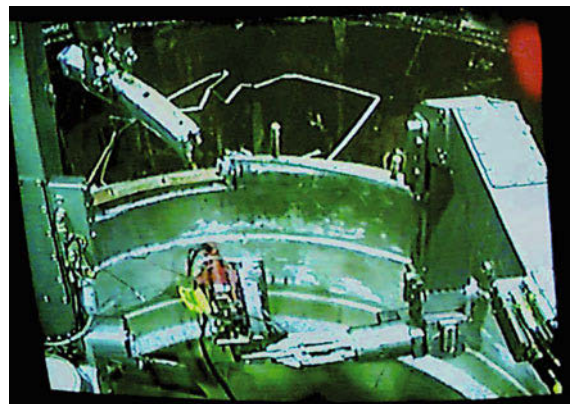


Fig. 58.16 Operator's view of a remote sawing task (courtesy of Oak Ridge National Laboratory)

Applications in Large Scale Science Experiments

High radiation levels resulting from materials activation in the target areas of high-energy particle accelera-

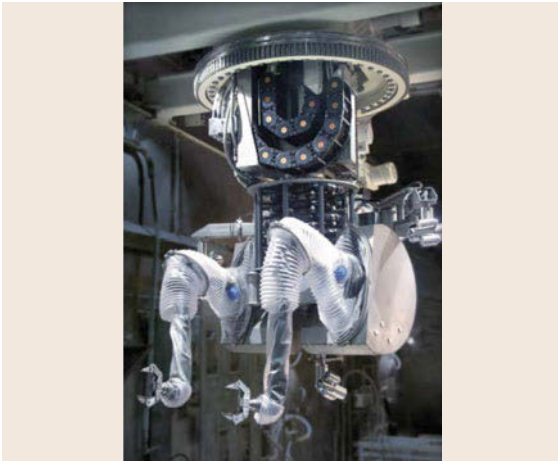


Fig. 58.17 SNS Telerob EMSM-2B Dual arm servomanipulator



Fig. 58.18 SNS Telerob EMSM-2B master control station

tor experiments often require remote operations. Since these are unique scientific experiments, they involve complex and specialized equipment that results in some of the most challenging remote operations in the world. Nonetheless these highly specialized remote operations still involve the basic elements of remote operations summarized in Fig. 58.1. The most recent example of this class of remote systems is the comprehensive remote handling system developed as an integral part of the Spallation Neutron Source (SNS) located at the Oak Ridge National Laboratory [58.55].

The SNS is a neutron scattering facility in which uniquely high-flux neutron beams are generated by impinging high-energy protons on to a mercury target. The mercury is activated to the extent that the contact dose rate in the associated piping and vessels can be over 10^5 R/h and are long lived. The design and operation of this target system are such that it must be periodically replaced or refurbished. The mercury tar-



Fig. 58.19 SNS remote handling control room



Fig. 58.20 SNS pedestal manipulator system

get system and its support infrastructure are located in a shielded hot cell that includes a comprehensive remote handling system. The hot cell remote handling system is comprised of combinations of conventional mechanical master/slave manipulators, overhead cranes and a state of the art dual arm telerobot. Details of the overall system are provided in [58.55]. The focus of this discussion will be the telerobotic system.

Figures 58.17 and 58.18 show a dual arm force reflecting servomanipulator system, Telerob EMSM-2B, that is mobile in 3-D throughout the hot cell by virtue of a overhead bridge (X,Y motions) and rigid telescoping tube (Z motion). The manipulators are 6 dof and each have a 245 N continuous capacity and 445 N peak capacity. A 2200 N auxiliary hoist is integrated into the bridge trolley to facilitate handling heavy objects with the telerobot. The bridge system can be teleoperated or robotically pre-programmed. A second dual arm servomanipulator package (Fig. 58.20) is part of a mobile pedestal mounted system that is specifically designed in the high bay area over the target hot cell. The control room, Fig. 58.19 includes 21 flat panel displays



Fig. 58.21 Fukushima Daiichi Nuclear Plant after tsunami had inundated entire site to depth of over 13 m and subsequent hydrogen explosions. (courtesy of Japan Atomic Energy Agency)

that can be used with any of the 11 remote cameras located in the hot cell. The telerobot operator is located at the far end of the room and can operate either standing or sitting. This overall system is functionally similar in concept to advanced servomanipulator systems discussed in the earlier sections. The system has been in operation since 2006 and has been successfully used in several major mercury target diagnostic/refurbishment campaigns. The SNS remote system has shown that the electromechanical equivalent of traditional MSM's with full remote hot cell mobility is practical and reliable. Larger scale nuclear facilities involving higher level of radiation are certain to follow the remote handling philosophy represented by this system. Because this class of electrical servomanipulators have all of the real-time digital control features of modern robots, greater use of programmed and intelligent control concepts for certain types of remote tasks is expected in future.

58.2.3 Lessons Learned from the Fukushima Daiichi Disaster

Japan has not only been at the forefront in the development of robots to help in disaster situations, but has also, sadly, experienced a major recent disaster of the kind anticipated by robotics researchers and engineers for decades previously. This disaster provided a reality check for researchers and exposed just how far we still need to progress before robots can be relied upon to perform routinely in hazardous environments.

The March 2011 tsunami precipitated the Fukushima Daiichi nuclear reactor disaster (Figs. 58.21 and 58.22). Even though the reactors were shut down at the time, they still required significant cooling water supplies as they had been only recently shut down.



Fig. 58.22 Underwater reconnaissance robot being evaluated in search for human remains following the March tsunami, Japan. (courtesy of Prof. Shigeo Hirose)

The tsunami destroyed the diesel back-up generators required to keep the cooling water pumps operating. The resulting temperature rise in the reactors led to gas explosions that severely damaged the reactors, their cooling systems and the containment buildings, spreading radioactive contamination over a large area of nearby land and ocean.

As Kawatsuma and his colleagues explained, many different kinds of robots had been developed as a result of earlier research and development programs [58.56]. Unfortunately, at the time of the disaster most of these robots were either inoperative, unable to be repaired and made ready, or unsuitable because of the need for tether cables, or reliance on Wi-Fi communications which could not be operated satisfactorily in the contaminated nuclear environment (Chap. 60.4). Several teleoperated construction machines developed for

the 1991 Mt. Fugen volcanic disaster were successfully deployed to clear contaminated wreckage and debris [VIDEO 578]. Robots originally developed for reconnaissance work, primarily investigation of unexploded ordnance, were supplied by British and American sources [VIDEO 579], [VIDEO 580], [VIDEO 581]. However only limited operations could be completed with these robots as they could not reach many of the places where they were needed. In the first months following the disaster, only one robot, the Japanese designed Quince from Chiba Institute of Technology, was successfully deployed inside the reactor buildings for several weeks before it failed with a wiring fault. At the time of writing, it had not yet been recovered for repairs [VIDEO 582], [VIDEO 584]. Since then more robots have been successfully deployed to the site, though still with limited operational capabilities.

The disaster exposed the need for prior planning and continuous training, rehearsal and cooperation between research and development agencies, defence disaster relief agencies, robotic systems manufacturers and engineers at the hazardous facilities where the robots

would be used. Rather than individual robots, systems of which robots form a part need to be developed, including shielded vehicles to allow close-up monitoring and control by human operators [VIDEO 583]. Continuous updating of robot systems is needed: some robots that could have been deployed relied on obsolete electronic and computer components that could not be replaced. Following this disaster, we can expect a significantly increased effort to deploy robots over the coming years to deal with the consequences of similar events.

The Fukushima Daiichi disaster and other operations following the March 2011 tsunami demonstrated that, as in the other applications discussed above, robots can still only be expected to perform a niche role. Robots have only performed consistently in such environments after decades of development, and investment in developing trained operators with appropriate maintenance and support facilities. Our ability to realistically predict the capabilities of robotic operations in unforeseen hazardous environments is still very limited.

58.3 Enabling Technologies

There are a number of technology issues that are key to the design and implementation of mobile robots that can operate effectively in different types of hazardous environments. A few of them are touched upon here to give the reader additional insight into the foundational aspects of this class of robots.

58.3.1 Mobility Issues

Hazardous applications such as fire fighting, EOD, and demining require the ability to operate on uneven ground in indoor and outdoor environments where a normal wheel-type robot cannot easily operate. Most mobile mechanisms are classified into wheel type [58.57–60], track type [58.61–66], and leg type [58.67]. For negotiability in uneven ground, the wheel and track types need additional linkages with ground adaptation. There are two kinds of this adaptation: active and passive adaptation. Active adaptation uses an additional actuator to alter the linkage's motion while in passive ones the linkage motion is controlled by the ground conditions and gravity effects.

Stability Conditions

Stability should be considered in the design process to prevent rollover on uneven ground including stairways, steps, and natural terrain. Stability can be investigated

in terms of three parameters: *center of mass*, *supporting area*, and *stability margin*. Static stability requires that the center of mass remains inside the supporting area, as shown in Fig. 58.23. The supporting area is a polygon built by the edges connecting each contact point on the horizontal plane. A conventional vehicle has limitations in rugged terrain due to a fixed center of mass with respect to the body coordinates. The center of mass greatly affects the stability margin (the minimum length between the center of mass and edges of a supporting area). If the center of mass is located out

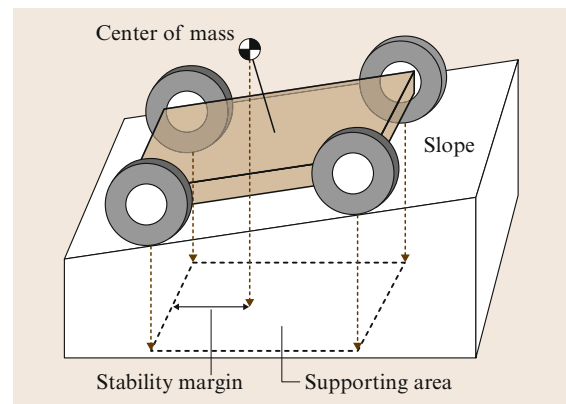


Fig. 58.23 Stability condition

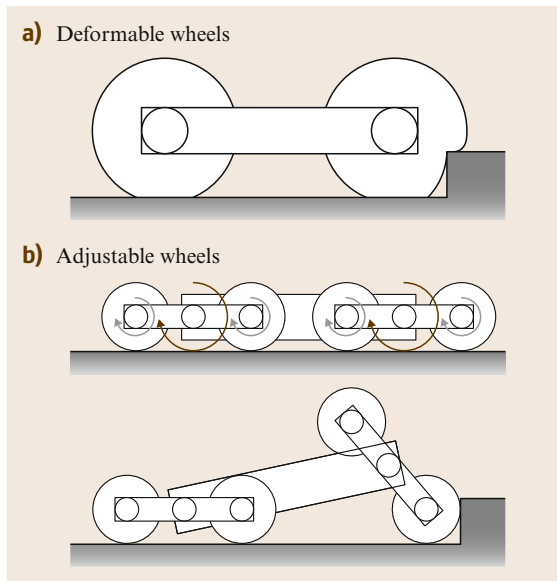


Fig. 58.24 Wheel configurations

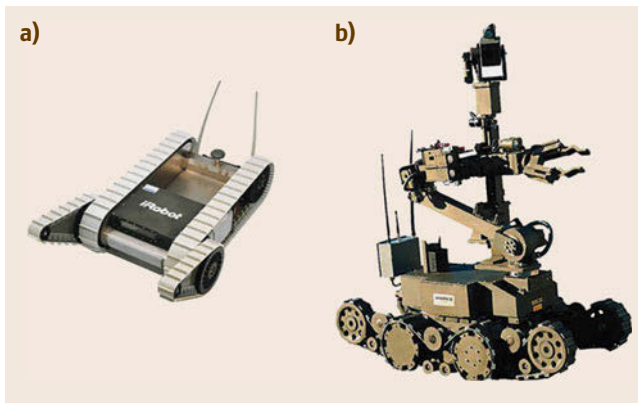


Fig. 58.25a,b Mobile robots with active adaptation mechanisms: (a) Packbot (after [58.68]), (b) Andros Mark V-A1 (after [58.64])

of the supporting area, rollover can occur. The stability margin of a conventional vehicle is mainly determined by the terrain inclination. Many vehicles are designed to have a low center of mass, thereby obtaining a large stability margin on a slope. Furthermore, a vehicle is often designed to have multiple bodies to overcome this limitation. For a multiple-link mechanism, the center of mass varies and the relative motion of links when traveling over the landform also alters the supporting area.

Active Adaptation Mechanisms

An active adaptation mechanism uses an additional actuator to generate motion of the adaptation linkage on rugged ground. Although additional actuators and

linkages are required, the adaptation mechanism can overcome variously shaped rugged landforms.

It is known that a vehicle can negotiate an obstacle which is smaller than the wheel radius. One may think that a vehicle which has large wheels can pass over rough terrain like a monster truck. However, most applications require a small vehicle to drive between obstacles.

A deformable wheel or its equivalent mechanism can be adopted: insufficiently inflated wheels, as shown in Fig. 58.24a, adapt to irregular terrain by deformation of wheels. However, their size should be big enough to negotiate rough terrain, so this concept still has size limitations. Their equivalent mechanisms are relatively compact and yet they need sophisticated articulation mechanisms, as shown in Fig. 58.24b. Two wheels are attached to a link that rotates about a main body. Therefore, revolution and rotation of wheels are made as shown in Fig. 58.24b. If rotation is provided by actuators at the main body (i.e., an active mechanism), the vehicle has an equivalent wheel whose radius is equal to that of the rotation. The vehicle in Fig. 58.24b can pass a step by carriage rotation, although the radius of a wheel is smaller than the height of the step.

Many track-type mechanisms have multiple linkage structures with active adaptation [58.63–66, 68]. When traveling over uneven ground, these mechanisms can negotiate rugged ground by changing the configuration of multiple track mechanisms, for example, typical multiple-tracked robots with active adaptation such as Andros [58.64] and Packbot [58.68], as shown in Fig. 58.25a and 58.25b, commonly uses a small active additional track called a flipper. When moving on relatively even ground the robot can reduce undesired track resistance by lifting up the flippers. When climbing up stairs, touching the flippers down to the ground can increase the stability by enlarging the supporting area. Snake-like robots use active interconnecting joints [58.65] and have the potential for mobility and manipulation.

Passive Mechanisms

Passive adaptation mechanisms do not use any additional actuators; rather they simply utilize the gravity effect to generate adaptation to irregular ground. This approach is less adaptive but enables the operator to drive the robot easily because he (or she) does not have to take care of controlling the adaptation mechanism. Passive mechanisms usually include various kinds of passive linkages activated by irregular ground conditions.

For the wheeled vehicle shown in Fig. 58.24b, a passive mechanism can be designed in which no additional actuators are needed, for example, when a wheel



Fig.58.26a,b Mobile platforms with passive adaptation: (a) Solero (after [58.60]) and (b) Robhaz-dt3

meets a sill whose height is greater than the radius of a wheel, it will become stuck. Then high torque is exerted at the wheel since the stall torque is usually greater than the normal rotation torque of the wheel. In this case, a closed linkage without any actuator except the driving wheels can generate a passive motion to climb over a step [58.58], for example, a smart mobile robot with passive adaptation called Solero (depicted in Fig. 58.26a) can climb up an obstacle by lowering the instant center of rotation of the passive four-bar linkage when coming into contact with the vertical surface of the obstacle [58.60].

Similarly, multiple bodies with tracked and chained passive joints can also adapt to irregular terrain. The track type is inherently insensitive to the unevenness of ground  **VIDEO 584**. Thus passively chained multiple-tracked bodies can provide greater reliability and better capabilities in ground adaptation. For example, a mobile robot with a passively chained double-tracked mechanism called Robhaz (shown in Fig. 58.26b) is a practical design with simply adapted multiple tracked bodies with passive joints [58.66]. As depicted in

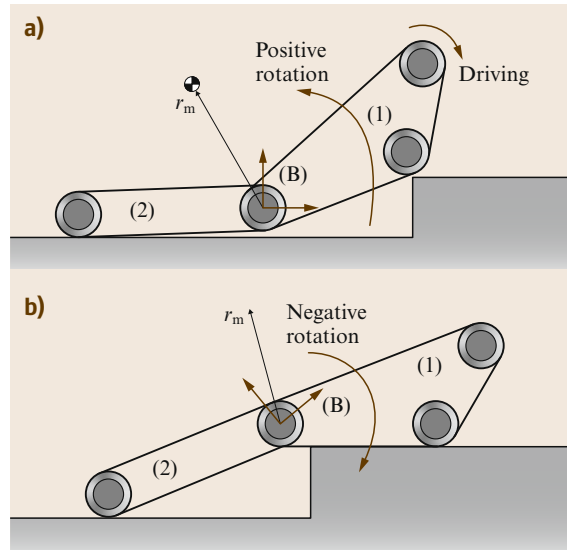


Fig.58.27a,b Passive adaptation of double-tracked mechanism: (a) positive deflection and (b) negative deflection

Fig. 58.26, two tracks of the Robhaz rotate positively or and negatively according to the contact situation between the track and the stair surface. Based on this behavior, in terms of the lower center of mass (Fig. 58.27a) and the supporting area (Fig. 58.27b) better stability in stair climbing than that of a single-tracked vehicle can be achieved.

58.3.2 Manipulator Design and Control for Hazardous Object Handling

Manipulation is essential for EOD missions. Generally, EOD missions have two phases: (1) approach, and (2) object manipulation to achieve ordnance neutralization. The second phase is generally controlled by teleoperation. Both the human's careful control and innate intelligence, plus appropriate manipulator design and control, are needed for such dangerous tasks.

Design Requirements

Unlike industrial manipulators, the design of manipulators for many robots in hazardous environments does not require very fast movement. Instead, high payload, light weight, and compactness are more important. Therefore, many manipulator designers locate actuators and reducers, which typically have high weight and large volume, on the base or lower links. This reduces the weight of the moving parts of the manipulator and offers better stability and dynamic control properties. Consequently, they have a thin profile, as shown in Fig. 58.28a,b. This characteristic is usually associated with explosive ordnance disposal-type robots that

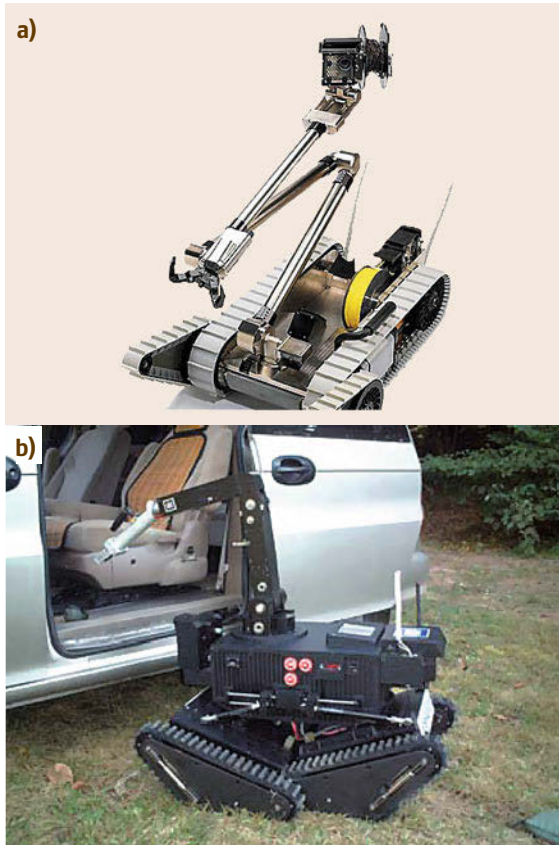


Fig.58.28a,b Hazardous application robots with manipulator: (a) Packbot with manipulator and (b) Robhaz-dt2 with manipulator

require access to congested areas and normal human living spaces. Mobile robots used in other hazardous environments can be much larger, depending on the specific applications.

58.3.3 Control for Hazardous Tasks

In most cases, the operator does not have much information about the environment around the robot and the manipulator. He may have very limited vision, and unexpected collisions between the manipulator and obstacles can easily happen, even if he (or she) tries to be very careful. The robot should be able to handle these risks by appropriate design of the manipulator and good control algorithms. There are several ways to solve these problems.

Proximity sensors that detect nearby objects can be used to avoid a collision before it occurs [58.69]. However using many proximity sensors necessitates large wiring bundles and complex manipulator design. Force control is also a good way to handle collisions.

When a collision occurs, the manipulator can move away from the collision point by using force/torque sensor data. Often a six-axis force sensor attached at the end-effector of the manipulator is used for the force control [58.70]. Many researchers have developed stiffness/compliance/impedance control methods for a manipulator with a force sensor. However, this method can only handle a limited collision zone – only the end-effector or the manipulator *hand* – because the sensor cannot sense contact with intermediate links, while a collision could occur at any point on the manipulator. For this reason, some manipulators use joint torque sensors at all of their joints [58.71]. When using a joint torque sensor, contact at any point on the manipulator can be sensed, however, gravity compensation and errors in the transformation from the joints to the Cartesian space introduce further difficulties.

The stability of telerobotic systems, particularly when force feedback or reflection is involved, remains a critical issue. Systems involving significant data communication time delays are even more difficult. National Aeronautics and Space Administration (NASA) groups have studied stability and bandwidth issues numerous times over the years; one of the more recent studies is provided by Uebel et al. [58.72]. Energy methods have been applied to this problem showing promise for enhanced stability and performance [58.4, 73].

Master Controllers for Teleoperated Manipulation

In teleoperation, the robot is designed to be a faithful slave to deal with a dangerous task while the operator uses a control interface to direct the slave from a safe location. The user interface usually provides a means for:

- Sending position commands to the manipulator.
- Providing contact force feedback or force reflection to the user.

Ideally, the design goal of a user interface is to make it *transparent*, so the operator feels as if he or she is directly manipulating the object handled by the slave manipulator. To achieve this transparency, there are several design issues:

- Simplicity:
 - All indicators are unified as one scene.
 - All input button and joystick are integrated into one haptic device.
- Intuitiveness:
 - High-level command by speech recognition.
 - Human-friendly feedback such as graphical displays and human voice.

- Motion command matching between the haptic device and the slave in Cartesian space.
- Portability:
 - Small/lightweight and human-friendly design for wearability
 - Tetherless operation without communication lines and additional power.

An example of wearable multimodal user interface is provided by [58.74], as shown in Fig. 58.29. The operator wears a head-mounted display (HMD), head tracker, and headset to interact with the slave. A six-degree-of-freedom haptic master is attached on his waist together with the standalone controller, and the operator grips its handle to telemanipulate in Cartesian space. With wearable hardware, the user can walk around to gain a better view during teleoperation using wireless communication. It is composed of major three operator interfaces.

Speech and Auditory Interfaces

An operator usually sends two types of commands to the robot: selection and continuous motion commands. For example, the selection between mobile and manipulation mode, the reset of the robot arm and mobile base, the on/off and reset of pan-tilt motors, speed selection for the mobile platform, selection among installed cameras are defined in the selection commands. Voice commands offer convenience. When the operator says a word that has been predefined as a command, the speech interface can sense that word and, if the speech recognition system successfully recognizes it, the recognized command pops up on the HMD for confirmation. Finally, the operator decides whether to execute or cancel the command with a confirmation button on the haptic master.

The auditory interface synthesizes the human voice using a speech synthesis engine. It can warn of the approach of an obstacle by sound, or reveal the distance and direction to a laser-designated object nearby.

Wearable Haptic Interfaces

A wearable haptic device is shown in Fig. 58.29. The base linkage is designed as a serial RRP mechanism to measure a translation, and an RRR z - y - z rotation mechanism is attached at the end of the base linkage.

Figure 58.30 shows a wearable haptic master device for teleoperation of mobility and manipulation systems. It has six degrees of freedom for motion input and three degrees of freedom for force feedback.

To achieve a compact design and reduce its weight, a tendon-driven mechanism is designed into each joint. Due to weight constraints, only three actuators are installed for force feedback, and each actuator is specially

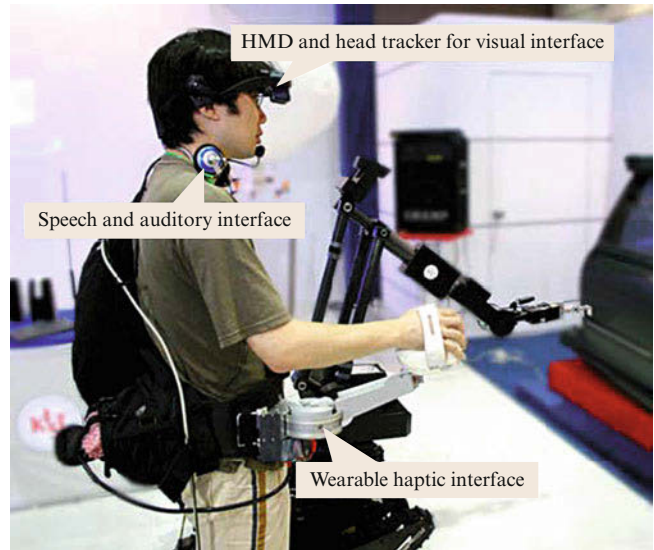


Fig. 58.29 Appearance of wearable multimodal user interface

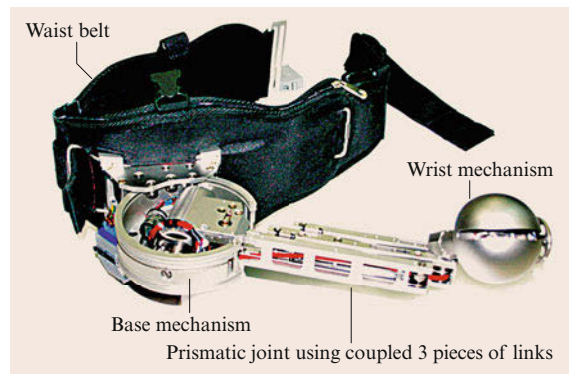


Fig. 58.30 Picture of wearable haptic device

designed to fit the joint. Because a passive actuator is better than an active actuator with respect to power density (power per unit volume or weight), small magnetorheological (MR) brakes have been developed. They are installed at each joint of the base linkage for force feedback. Also a compact brake drive with current feedback capability has been designed, which reduces the response time of the MR brake. The controller is packed into a bag that is attached to the back side of the waist.

Visual Interfaces

The visual interface integrates the robot's view, the status of sensed data, and the status of speech commands. Since the slave includes a stereoscopic camera, the user sees a three-dimensional view on the head-mounted display (HMD). The operator wears a head tracker and it generates a pan/tilt command from the two-degree-of-

freedom head motion. In the integrated system, head tracker data is used to command the direction of the remote viewing camera, thus the user easily looks around the environment of the robot, as shown in Fig. 58.31.

Moreover, the head tracker is useful to indicate an object as a target. The operator moves his head and looks at a target to get information of direction and distance, then triggers a laser displacement sensor that is placed in parallel with the pan-tilt camera. A virtual reality overlay is prepared with the reported data, as shown Fig. 58.31. The recognized speech command is highlighted on the left for confirmation. These are overlaid on the remote video source pictures and unified into a single scene. Finally the operator sees the stereoscopic picture and the status of the robot at a glance on the immersive HMD. The overlaid view is shown in Fig. 58.31c.

58.3.4 Data Communications

Robots used in hazardous environments are almost always mobile so that they can move about an area of interest with flexibility. The combination of mobility and intrinsic operation across a physical or hazard barrier introduces unique problems with respect to bidirectional data communications (Fig. 58.1). Communications from the operator location to the robot is necessary to achieve remote control or teleoperation. Communi-

cations from the robot to the operator are essential for situational awareness. The transmission of the electrical and/or optical signals comprising such data communications can be quite complex due to a host of factors such as penetration of physical barriers, signal transport delays, signal attenuation, and data throughput requirements. Data throughput requirements are dominated by the feedback of visual imagery or remote camera views from the mobile system. Channel capacity necessary for audio feedback and control are small in comparison. If the mobile system involves precision manipulation with force feedback, bidirectional data channels on the order of 1 Mb/s are required.

For a mobile robot with high-fidelity manipulation, multichannel remote viewing, and other sensors, on the order of hundreds of Mb/s are required for the data communications path from the remote environment to the operator station while on the order of ten Mb/s are needed for the bidirectional control link. Data throughput requirements can be reduced through data compression hardware provided there is no significant increase in latency (time delay) which can degrade control by humans if the delay exceeds 100 ms. The choice of communication means is not easy: while wireless communication seems attractive, when multiple robot systems need to cooperate in a shared space, the communication systems need to be designed with this in mind. All too often, communication systems have evolved to support only a single robot system within a given operating region. Tethered cables provide high bandwidth, but pose extreme difficulties in unstructured environments, and when multiple robot systems need to work together (Table 58.1).

58.3.5 Energetics

Another key challenge in fielding mobile robots in hazardous environments is in the area of energetics including power supply, consumption, conversion, and management. The specifics of the given environment often restrict the types of power supply/conversion that are permissible, for example, the use of combustible fuels and internal combustion engines is seldom allowed within coal mines, refineries, gas plants, offshore platforms and nuclear facilities but can be entirely acceptable in demining and other outdoor operations. The most common power systems used for research robots are electrochemical batteries and electric motor drives. The power and energy density map [58.75] given in Fig. 58.32 shows the fundamental situation for mobile robots used in hazardous environments. For perspective, a small passenger automobile is estimated to need a minimum of 200 Wh/km to meet road demands, which in turn translates into 500 Wh/kg. This

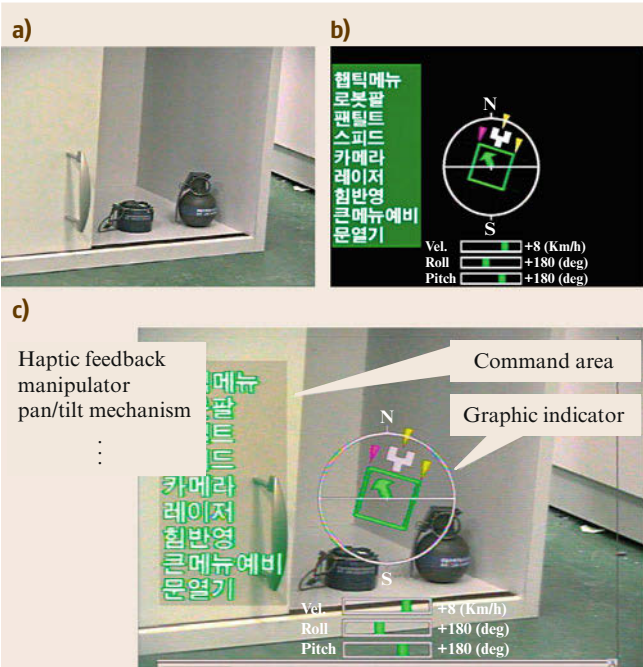


Fig. 58.31a–c Appearance of integrated visual interface: (a) camera view (b) overlay source view (c) user view

Table 58.1 Example data communications requirements (minimum)

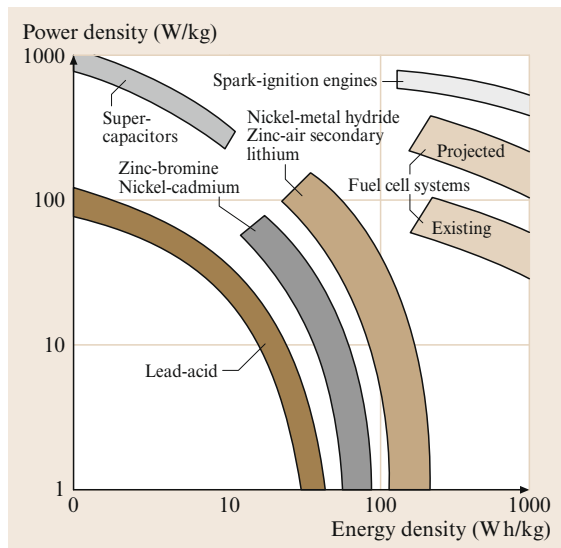
Type	Single channel resolution	Typical standard system
Standard black-and-white remote television (typical for rad hard technology): 600 × 400 pixels 30 frames/s 12 bit gray scale	≈ 10 Mb/s per viewing channel	30–50 Mb/s for 3–5 channels
Color remote television: red, blue, and green = 3 × black and white	≈ 30 Mb/s per viewing channel	90–150 Mb/s for 3–5 channels
Color high definition (HD) 1080p television: 1920 × 1080 pixels 60 frames	~ 1.5 Gb/s per viewing channel with encoding compression ~ 3 Gb/s uncompressed	5.5–15 Gb/s for 3–5 channels
Control 12 bit resolution input and output 200 Hz sampling rate	≈ 4.8 kb/s per control channel	48 kb/s – ten control servo channels
Audio feedback 15 kHz signal capture 12 bit resolution	≈ 180 kb/s per audio channel	540 kb/s – three remote micro-phones

is why hybrid electric vehicles that combine spark ignition engines with battery-powered electric motors are becoming popular. A large mobile robot with dual manipulators operating in the payload range of hundreds of kg would have power requirements similar to these and would be well above the 100–200 Wh/kg range that batteries can provide. A force-reflecting six-degree-of-freedom robot manipulator with a 20 kg payload will have a peak power consumption on the order of 10 kW. If a particular application domain is amenable to the use of spark ignition engines, the order of magnitude of power density compared with any type of battery-powered system makes implementation feasible. If pure battery power is necessary, then considerable attention

must be given to the design, including state of charge monitoring and mission provisions for recharging. In the future, emerging fuel-cell technology may provide better solutions for mobile robot power systems.

58.3.6 System Architectures for Real-Time Mission Control

Because of the intrinsic nature of hazardous environments where uncertainty and lack of geometric structure are prevalent in the task environment, shared control architectures are commonly used. The degree of human interaction runs the gamut from pure teleoperation (manual control) to high-level intelligent control operations (autonomous). For example, most low-cost EOD type robots utilize simple manual control architectures, while at the other end of the spectrum, the Mars rovers operate as autonomous agents responding to mission-level commands from human operators on the earth. The basic architectures for real-time mission control are summarized in Fig. 58.33 [58.76]. Also, see *Sheridan* for a comprehensive discussion of architecture principles and design [58.44]. Between the manual and autonomous control exist combinations of computer assistance and semiautonomous (i.e., selective and in situ task automation) functions intended to improve remote work performance by either reducing operator workload or allocating tasks more suitable for computer control to autonomous execution. It is important to recognize that, as one moves from manual control toward autonomous control, the data throughput rates for communication and control are reduced because high-level commands are comparatively small packets of information while force-reflection manual control of a manipulator, for example, requires visual feedback and high-bandwidth control interconnection

**Fig. 58.32** Power and energy density for various power storage and supply systems

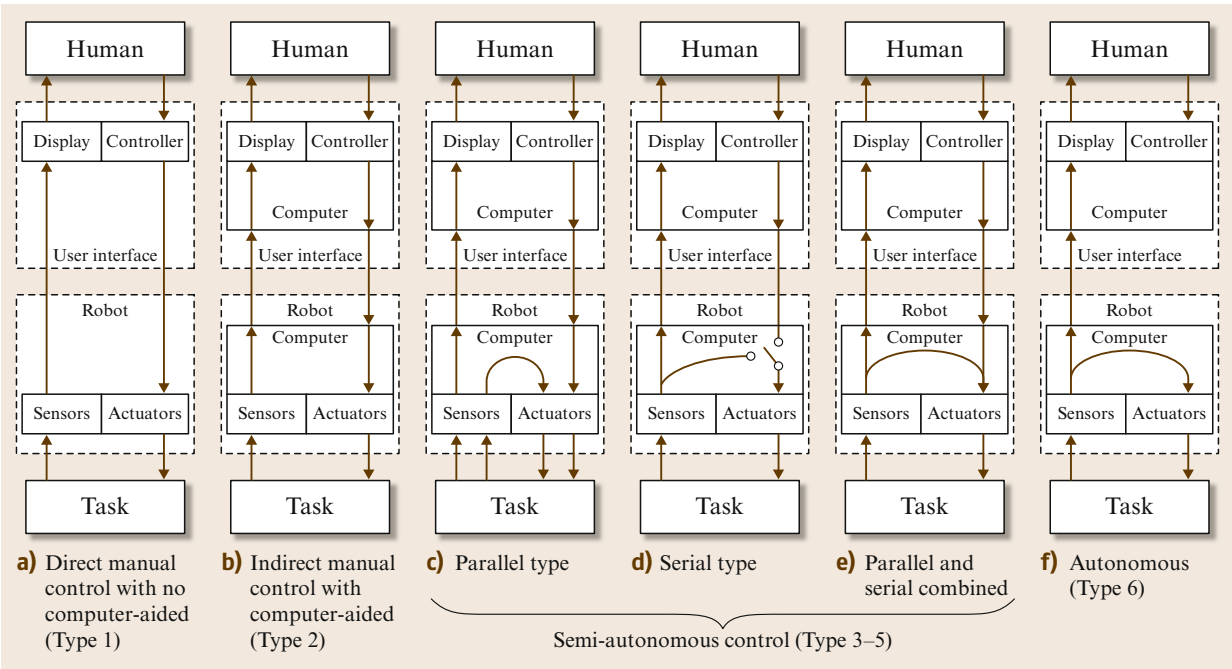


Fig. 58.33 System control architectures

of the slave and master controller. The data communication bandwidth available influences control architecture. Untethered undersea applications usually require semiautonomous architectures because of the bandwidth limitations of acoustic communications links.

As intelligent systems research advances, it is expected that, for hazardous situations, robots will em-

ploy semiautonomous and autonomous architectures to a greater degree as a fundamental approach to overall performance optimization. Operators will be able to choose the control mode based on the task needs and the likelihood that autonomous execution can be reliably achieved. In this human-centered way, task execution mode will be matched to best achievable performance.

58.4 Conclusions and Further Reading

If we are to learn anything from the experience of the last decade we must appreciate that robotics research is just one step in the development of tools that extend human capabilities. This search for improved tools is as old as humanity itself, so great patience is required [58.77].

Researchers need to make significant advances on four different fronts: mechatronics design, sensing, machine intelligence, and problem understanding:

- Mechatronics designers have to trade gains in precision, dexterity, mobility, and strength for losses in endurance and reliability. We are mostly well short of biological (e.g., human) capabilities except for high-precision applications. Machines have much the same environmental tolerance as people. Machines need special precautions against
- heat and cold outside the temperature range of 0–35 °C, and operation beyond –60 or +60 °C is usually impractical. Dust, radiation, low or zero air pressure, fumes, biological agents, even insects can be fatal for machines without special design features, which may result in performance reductions. Maintenance or repair work may necessitate decontamination before people can work on the machinery.
- While electronic sensors can go far beyond biological capabilities, hazardous applications still present problems far beyond present capabilities as we have seen in the case of landmine applications. Radiation levels that are lethal for humans can also quickly kill electronic sensors. Extreme heat or cold limits sensor performance, as can contamination, and even insects.

- Advances in usable machine intelligence have been much more difficult than many expected. The only real progress has been achieved with capabilities often associated with clever people: logic, mathematical manipulation, and playing games. While recent advances have enabled a remarkable degree of understanding for some insect perception and motor capabilities, the social behaviour of insects still largely defies present-day understanding. However, teleoperation and supervisory control can make up for this deficit in the medium term. Shortcomings in machine intelligence represent less of a barrier than the other three fronts.
- Understanding the intended application and economic factors has proved to be equally important for researchers. Early success from exploiting specific opportunities can generate confidence that inspires others to persevere with more difficult general problems. Failures in understanding the desired task performance, particularly with respect to economic factors, can undermine confidence and the credibility of research efforts. Attempts to develop landmine clearance robots provides a useful case study that illustrates some of the difficulties in developing robots for hazardous applications.

There is no question that future teleoperators will become hybrid telerobotic systems that allow seamless transfer between manual and autonomous operations. Specific tasks will be selectively automated by operators for the purposes of enhancing quality and/or reducing subtask execution times. Early systems will continue to incorporate high levels of human interactivity to accommodate the limitations of current intelligent systems technology. Real-time execution of complex control algorithms and virtual-reality-like graphics engines (which are really useful) have become routine. Robust machine learning that allows human task execution skills to be captured through learning by observation or imitation is gradually becoming realizable. Advances in mass production of microelectrical mechanical systems (MEMS) technologies has greatly reduced the cost of sensing devices. In the next decade, telerobots for hazardous environments will become smarter and their relationship with their human operators will become more cooperative and less interactive. Human operators will supervise the operation of multiple telerobots: at the moment, the number of support people required for real operations is a multiple of the number of robots.

Readers are directed to the selection of references provided in this chapter for further reading.

Video-References

-  **VIDEO 571** UNMACCA: Demining Afghanistan
available from <http://handbookofrobotics.org/view-chapter/58/videtails/571>
-  **VIDEO 572** IED hunters
available from <http://handbookofrobotics.org/view-chapter/58/videtails/572>
-  **VIDEO 574** Bozena 5 remotely operated robot vehicle
available from <http://handbookofrobotics.org/view-chapter/58/videtails/574>
-  **VIDEO 575** DALMATINO
available from <http://handbookofrobotics.org/view-chapter/58/videtails/575>
-  **VIDEO 576** PT-400 D:Mine
available from <http://handbookofrobotics.org/view-chapter/58/videtails/576>
-  **VIDEO 577** DIGGER DTR demining destroying anti-tank mines
available from <http://handbookofrobotics.org/view-chapter/58/videtails/577>
-  **VIDEO 578** Remote-control heavy equipment used in debris removal at Fukushima reactor 3
available from <http://handbookofrobotics.org/view-chapter/58/videtails/578>
-  **VIDEO 579** iRobots used to examine interior of Fukushima powerplant
available from <http://handbookofrobotics.org/view-chapter/58/videtails/579>
-  **VIDEO 580** iRobots inspecting interior of Fukushima powerplant
available from <http://handbookofrobotics.org/view-chapter/58/videtails/580>
-  **VIDEO 581** Robot being used to carry vacuum cleaner head at Fukushima powerplant
available from <http://handbookofrobotics.org/view-chapter/58/videtails/581>
-  **VIDEO 582** Views of robot control screen – inspecting Fukushima power plant
available from <http://handbookofrobotics.org/view-chapter/58/videtails/582>
-  **VIDEO 583** Promotional video of robot for cleaning up Fukushima
available from <http://handbookofrobotics.org/view-chapter/58/videtails/583>
-  **VIDEO 584** Sukura robot developed for reconnaissance missions inside nuclear reactor buildings
available from <http://handbookofrobotics.org/view-chapter/58/videtails/584>
-  **VIDEO 586** HD Stock Footage 1950s atomic power plants – nuclear reactors
available from <http://handbookofrobotics.org/view-chapter/58/videtails/586>

-  **VIDEO 587** Radioactive material handling 1954
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/587>
-  **VIDEO 588** Nuclear manipulator remote handling equipment (1960)
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/588>
-  **VIDEO 589** 1961 nuclear reactor meltdown: The SL-1 accident – United States Army Documentary
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/589>
-  **VIDEO 590** Jean Vertut master-slave manipulator arms
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/590>
-  **VIDEO 591** NanoMag magnetic crawler for remote inspection
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/591>
-  **VIDEO 592** Remote handling and inspection with the VT450
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/592>
-  **VIDEO 593** Robots answer nuclear waste challenges at SRS
available from <http://handbookofrobotics.org/view-chapter/58/videodetails/593>

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Multimedia Contents



59. Robotics in Mining

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This chapter presents an overview of the state of the art in mining robotics, from surface to underground applications, and beyond. Mining is the practice of extracting resources for utilitarian purposes. Today, the international business of mining is a heavily mechanized industry that exploits the use of large diesel and electric equipment. These machines must operate in harsh, dynamic, and uncertain environments such as, for example, in the high arctic, in extreme desert climates, and in deep underground tunnel networks where it can be very hot and humid. Applications of robotics in mining are broad and include robotic dozing, excavation, and haulage, robotic mapping and surveying, as well as robotic drilling and explosives handling. This chapter describes how many of these applications involve unique technical challenges for field roboticists. However, there are compelling reasons to advance the discipline of mining robotics, which include not only a desire on the part of miners to improve productivity, safety, and lower costs, but also out of a need to meet product demands by accessing orebodies situated in increasingly challenging conditions.

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There was a time, in recent history, when improved productivity and lower mining costs could be achieved purely by the economies of scale that arise from the use of larger equipment [59.1]. However, this era is likely over. Today's mining companies and equipment manufacturers have been making renewed efforts in the

pursuit of new and innovative approaches to the business of resource exploration and mining. Among these efforts has been a move toward increasingly autonomous mobile equipment and processes. For example, major suppliers of mining equipment for both underground and surface mining operations now offer

robotic driving, dumping, and other materials handling functionalities. What is more, some global mining companies are now operating their own technology-focused divisions, each with goals of bringing new technological developments to their mines worldwide.

Finally, there exist several emerging frontiers for mining, where robotics is already playing a critical role. These include not only very deep and high altitude mining, but also undersea mining and extra-terrestrial mining.

59.1 Modern Mining Practice

Mining is an ancient and broad practice, dating back to Palaeolithic times (43 000 years ago) [59.2] and involves the extraction of materials from the Earth's crust for utilitarian purposes. Today we mine minerals (e.g., gemstones, metals, salt, coal, and many others), aggregates, natural gas, and petroleum. These resources are used, for instance, to make the tools we use, shelter, food products, medicine, and clothing. Try to imagine, for a moment, a life where you endeavored to use (or build a robot from) absolutely nothing derived from mining. We benefit greatly from mining, but there is also increasing pressure and international recognition that the often negative environmental, safety, and social implications of mining and mineral processing must be curtailed and balanced with economic and lifestyle considerations. Robotics can play a vital role in all of these efforts.

In this section, we briefly provide some introductory background about the fundamental stages of mining, common to most operations, and discuss what drives the field of mining robotics, as well as its unique challenges, technical and otherwise.

59.1.1 Stages of Mining

Almost all mining operations have five fundamental stages [59.3]:

1. Prospecting
2. Exploration
3. Development
4. Exploitation
5. Reclamation.

Prospecting involves the initial search for valuable materials. This stage is normally carried out by geologists, and deposits may be located at or below the surface. Prospecting usually happens by either direct visual examination or by indirect methods (e.g., through the use of geophysical techniques) that look for anomalies in seismic, magnetic, electrical, electromagnetic, and/or radiometric variables of the Earth. Geochemistry and geobotany techniques are also employed. Although robotics has not yet played a pivotal

role in the search for minerals on the Earth, planetary geologists have been collaborating with roboticists for planetary prospecting; e.g., [59.4] and references therein.

In the *exploration* phase, the objective is to determine as accurately as possible the size (*tonnage*) and value (*grade*) of a deposit. This process is sometimes called *delineation* and more often than not involves collecting samples of material by drilling. Similar to prospecting, robotic exploration drills for mining are not yet common for surface exploration on the Earth. However, there has been a significant amount of work on robotic drilling in extreme environments, such as undersea and planetary exploration; see [59.5] for a good introduction and ample references.

The development and exploitation phases of mining are where tools and techniques from robotics have been, to date, applied most. *Development* is the work necessary to bring a mine into production, and usual entails planning, design, construction (e.g., overburden removal, shaft sinking, underground access) and the installation of mine services (e.g., power, water, ventilation, etc.).

It is during the *exploitation* phase that the resource is physically extracted, processed, and shipped to buyers. How exploitation occurs depends on the selected *mining methods*, which depend on many factors. These include the spatial characteristics of the deposit, geologic conditions, geotechnical conditions, economic considerations, technological considerations (e.g., the availability of advanced tools), and environmental considerations. Generally speaking, mining methods can be divided into two categories:

1. Surface mining methods;
2. Underground mining methods.

Surface-mining methods are used when the deposit lies near the surface, are usually very large scale operations and have high production rates. Underground methods are used when the deposit is deeply buried. Such methods have lower production rates and are usually more technically challenging and hazardous for mine workers.

Figure 59.1 shows examples of robotic vehicles used in surface and underground mining. These technologies, among others, are discussed further in Sects. 59.2 and 59.3.

Mining must strive to meet the economic and environmental needs of the present while at the same time ensuring (or enhancing) the ability of future generations to meet their own needs. Mine *reclamation* is the process of closing a mine, recontouring, revegetating, and restoring the land and water to an acceptable post-activity state. The objective is to minimize any adverse effects on the environment or threat to human health and safety. Some reclamation activities involve the construction and monitoring of *tailings* impoundments, where waste from mining and resource processing activities is placed.

Recently, tools from robotics have been used to conduct bathymetric surveys of tailings ponds, which are unique environments with very specific safety requirements. Figure 59.2 shows a robotic maritime research vessel performing a bathymetric survey of a mine tailings pond at a potash mining operation in eastern Canada. Performing robotic surveys has been shown to be safer and more cost-effective [59.6].

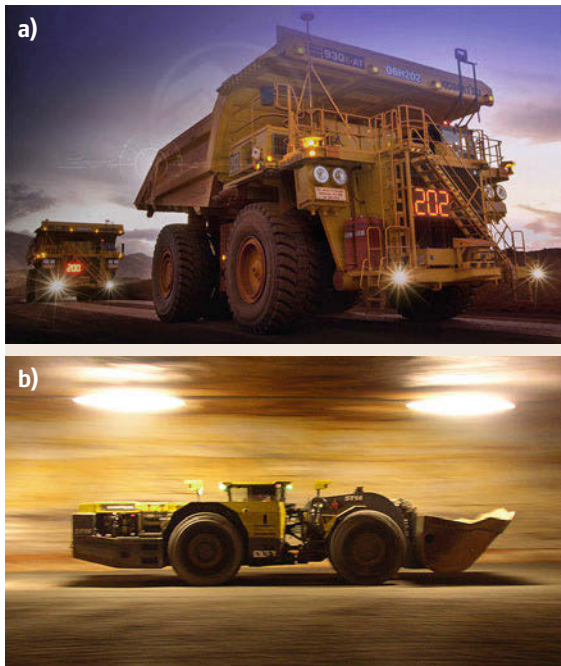


Fig. 59.1 (a) Examples of robotic vehicles in underground and surface mining. Unmanned surface haul trucks (Photo: Mobular Mining Systems, 2011); (b) an autonomous underground load-haul-dump (LHD) machine at the Kvarntorp mine, Sweden (Photo: Joshua Marshall, 2007)

59.1.2 Technology Drivers in Mining

In order to better understand the potential for applications of robotics in mining, one must appreciate what drives the development of equipment technology in the mining industry. Mining is a dynamic process that must deal with the uncertainties of *outdoor* environments, and is usually conducted in as a series of interacting unit operations (e.g., drilling, blasting, loading, hauling, and processing). The harsh, extensive, and unstructured environments found in mining often preclude the application of existing techniques from other industries (e.g., from manufacturing robotics) [59.7, p. 806]. However, the recent growth of mobile and field robotics has resulted in several opportunities for robotics in mining. These opportunities stem mainly from a set of primary technology drivers:

- **Working Environment.** Mines are often developed in harsh and remote areas. For example, several companies operate mines and processing facilities at high altitudes. Also, as mines strive to operate at greater depths, extremely high ambient temperatures and humidity pose greater health risks [59.8]. Robotics may serve to minimize infrastructure needs and physically remove people from such hostile environments.
- **Labor Shortage.** Miners have reported difficulties finding the skilled labor needed to support their operations [59.9]. The newest generation of workers is technologically astute, but holds a different attitude toward physical labor than previous generations. Robotization may be what is needed to entice this new generation into mining.
- **Health and Safety.** With increasing mine depths, growing equipment sizes and speeds, and the tight-

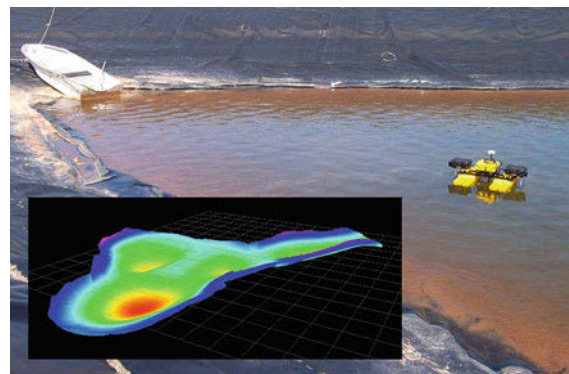


Fig. 59.2 Robotic maritime research vessel conducting a bathymetric survey of a mine tailings pond with overlaid example bathymetry map (Photos: Clearpath Robotics, 2013)

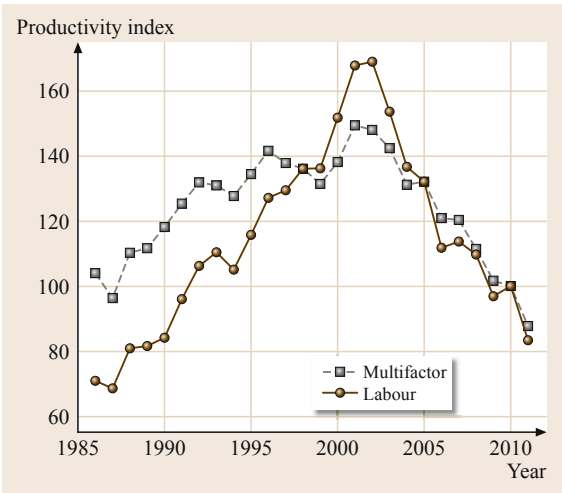


Fig. 59.3 Experimental estimates of multifactor and labor productivity for the mining industry in Australia (1986–2011) showing decreasing productivity since 2001 (after [59.10])

- ening of government regulations, it stands to reason that the deployment of almost any new technology that enhances the inherent safety of mining will be viewed positively at all levels.
- **Equipment Maintenance.** Maintenance costs and machine failures can make up a very significant portion of mine operating costs [59.11]. Moreover, operators often push equipment to its performance limits. Recent wisdom from the field of reliability engineering suggests that the automation (or

partial automation) of mobile equipment may help to significantly reduce downtime and maintenance costs [59.12].

- **Operational Efficiency.** There are a great number of areas in which efficiency improvements might be realized by the application robotics in mining. The most obvious lies in the fact that production time is lost during shift changes and breaks, resulting in much less than the desired 24/7 runtime. Not as obvious, and more difficult to quantify, is the less-than-optimal way in which underground mines typically operate. Without global and real-time control over the assignment (and movement) of machinery, the ability to optimize production performance through, for example, reduced dilution and increased recovery is also very difficult [59.1].
- **Sustainability.** Environmental and social responsibility are expected of modern mining companies and equipment suppliers. The alleviation of emissions (e.g., through the coordination and optimization of fleets) or reduction in power consumption by reduced operating demands (e.g., ventilation support) might be realized by way of real-time monitoring and automation of equipment.

Figure 59.3 shows multifactor and labor productivity for the mining industry in Australia between 1986 and 2011. Arguably encompassing all of the factors above, this data shows a worrisome decrease in productivity since the turn of the century, and some believe that robotics might help to reverse this trend [59.13].

59.2 Surface Mining

Surface mining is characterized by high tonnage operations, massive mobile equipment, and challenges that can include difficult environments (e.g., dust, fog, and extreme weather) together with remote locales and a strict need for keeping costs low.

59.2.1 Automated Haulage

Haulage is the process of moving material from one location to another. In the surface mining context, this is typically achieved using *haul trucks* (Fig. 59.1a), which move material from the point of blasting/excavation to the point of processing or stockpiling. The material being moved is either the desired economic quantity or overburden, and the destination is usually dependent on the load in the truck.

Haulage is a repetitive process, and the one to which automation can bring significant benefits, particularly

with respect to safety. Between 1989 and 1991, haul trucks were involved in 42% of the accidents and 60% of the fatalities in surface mining [59.14]. As with most mining equipment, there are also potential benefits of automation in the areas of productivity, repeatability, and reduced maintenance costs. Although it is too early in the history of robotic mining equipment to precisely define these benefits, the lessons from port automation (which use machines of similar scale, albeit in a more benign environment) have shown that maintenance costs of autonomous straddle carriers (in particular tyre wear and fuel costs) are reduced by approximately one-third [59.15] over their conventionally operated counterparts.

Autonomous Haul Trucks

Autonomous haul trucks can be thought of as mobile robots operating in a difficult, dynamic environment. As

such, they are required to have systems to address the standard issues of sensing and perception, situational awareness, localization, and control. The unique challenges presented in surface mining not present in other robotics applications include:

- Scale (haul trucks can carry up to 400 t of material).
- Mining pits often restrict the view of the sky, which can dramatically decrease global navigation satellite systems (GLS) reliability.
- Surface mining environments are constantly changing, which limits the ability to install fixed infrastructure.
- Mixed manually operated and automated fleets of machines, which places strict requirements on safety and integrity.
- All-weather operational requirements.

In the commercial sector, both Caterpillar and Komatsu had demonstrated the ability to automate haul trucks as early as the mid-1990s [59.16]. However, it was not until 2008 that the first commercial deployment of Komatsu driverless trucks was realised in the Gaby Mine, operated by Codelco in Chile [59.17]. This was followed closely by a deployment by Rio Tinto at their West Angelas mine in the Pilbara, Western Australia [59.18] ( VIDEO 145), where they have operated continuously since and have moved more than 50 million t of waste.

The Komatsu trucks operate using a high-precision global positioning system (GPS) as the primary localization sensor, radar sensors for obstacle detection and situational awareness, a proprietary wireless communications system, and are given tasks (load, haul, dump, etc.) using a proprietary scheduling system developed by Modular Mining Systems [59.18].

At the time of writing, similar systems by Caterpillar [59.19] and Hitachi [59.20] are also in various stages of trial and deployment, although there is scant information available publicly regarding the specifics of their designs and operation.

The automation of mining haul trucks is still an area of active research, however, primarily due to the challenging nature of the mining environment as previously noted. New positioning systems [59.21], situational awareness systems (Sect. 59.2.10), and planning and scheduling algorithms [59.22] are all under active development, and are intended to improve robustness, safety, and productivity, respectively. If each of these challenges can be addressed, robotic haulage technology will be able to be applied in a much greater range of operational scenarios than is currently possible.

59.2.2 Fleet Management

Fleet management is a catch-all term that may define a number of different technologies used in mining. Commonly though, fleet management is divided into three main tasks:

1. Position (and perhaps materials) monitoring
2. Production monitoring
3. Equipment task assignment.

Fleet management solutions are typically deployed to an office environment and allow operators to quickly survey large amounts of mine data so that appropriate actions can be taken in real-time on the mine-site. Computerized fleet management must integrate and evolve with the deployment of robotic mining machines.

Position Monitoring

The position of mobile equipment is commonly reported via wireless communications to a mine or region's database, where it can be queried by a visualization application. This provides a real-time picture of the movement of all equipment that has been enabled for such operation and allows an operator to quickly assess whether planned operations are proceeding as expected. Material movements may also be monitored in a similar fashion, but the material type (ore or waste) and grade must usually be entered manually by an operator. However some parameters, such as weight, are measured by the system.

Production Monitoring

Given that vast quantities of data may exist (particularly from robotic machines) that give a historical account of the evolution of a mine, or group of mines, this data can be used to provide detailed reports to mine management, and may also be useful as part of a continual productivity improvement process. Examples of production monitoring data may include machine cycle times, average maintenance cycles, machine failure events, payloads, or combinations of parameters (e.g., machine failure events vs. machine payload weight).

Equipment Task Assignment

At a typical mine, the equipment task assignment problem is addressed in a manner very similar to that of the urban taxi dispatch problem: A centralized authority decides, based on some predefined high-level goals, which machines must visit certain locations on the mine-site and perform some useful action. A machine

operator is generally given these instructions through a user interface located in the machine's cabin, which must be acknowledged and accepted prior to carrying out the task. The most typical implementation of the task assignment problem addresses the haulage scenario: when should a particular haul truck approach a given shovel, and when and where should it dump its subsequent load? Haulage is most commonly addressed, because it is here that even small changes in efficiency can have significant effects on overall profit.

Commercial Solutions

There are many commercial solutions for fleet management in the surface mining. The dominant solution is Modular Mining's DISPATCH system [59.23], which was developed in the 1970s. It implements an optimization algorithm to allocate trucks to shovels and dump sites, and contains modules for the other tasks of production and positioning monitoring. Modular Mining joined the Komatsu group of companies in 1996 and helped to deploy the FrontRunner autonomous haulage system described previously [59.24].

Other commercial systems include Caterpillar's MineStar software [59.25], Wenco's fleet management solution [59.26], Leica Geosystems Jigsaw suite of software and hardware [59.27], and Devex's Smart-Mine system [59.28]. These systems all now offer very similar overall functionality and differ mainly in implementation details.

Fleet Management Research

Although commercial systems for fleet management exist, there is still a substantial amount of research being undertaken, primarily in the area of task assignment optimization. Most commercial systems optimize task allocation using a heuristic that defines costs for allowing a shovel to become *idle* and/or allowing haul trucks to *wait* in a queue. In an ideal or optimal system, all items of equipment are fully utilized. However in practice, a higher cost is usually given to shovel idle time. The paper [59.29] gives a good overview of many of the commonly used heuristics used in task allocation optimization.

More recently, it has been acknowledged that heuristic, deterministic optimizers may not always produce truly optimal task assignments. This is primarily due to their inability to account for variability in the duty cycles of the items of equipment (i.e., they are stochastic rather than deterministic in nature), and any unforeseen discrete events, such as equipment failure, road blockage or operator error. The papers [59.22, 30–33] all describe recent approaches to overcoming these hurdles.

59.2.3 Robotic Digging

Mass excavation is one of the most important operations in mining. Being extremely sensitive to economies of scale and requiring a significant capital investment, it became a target application for robotic technologies starting in the mid-1990s. Surface mining typically uses large hydraulic excavators, hydraulic shovels, and electric rope shovels (Fig. 59.4). See also Sect. 59.3.3, which focuses on underground robotic loading.

Research in robotic digging involves systems design (including systems of systems), traditional robotics topics (sensing, planning, control), and tool-ground interaction problems. A framework for an intelligent earthwork system is suggested by [59.34], which discusses factors that can affect earthwork operation performance, identify key emerging technologies to support the implementation, the system architecture, and the system control strategy. A comprehensive review by [59.35] examined various aspects of sensing, planning, and control as they apply to earthmoving automation. Later developments in these topics are further discussed in [59.36]. Irrespective of the manned/unmanned aspect of the operation, a typical digging phase involves a number of critical steps: planning the bucket trajectory in contact with the ground, bank or muck pile; detecting when the bucket is full; and, detecting incipient stall and averting it. An analysis of autonomy requirements for each of these steps is detailed in [59.37] for the particular case of an electric rope shovel.

In other work, authors of [59.38, 39] proposed an autonomous excavation system for front-end-loader style machines that uses bucket force feedback, fuzzy logic, and neural networks for control. In their approach, a set of fundamental bucket action sequences,



Fig. 59.4 A rope shovel dumping into a haul truck (courtesy of Commonwealth Scientific and Industrial Research Organisation (CSIRO), 2006)

typically used by human operators, was compiled for use by the controller. A reactive approach, using fuzzy behaviours, was designed to act on force data to assess the excavation status and determine an appropriate control input. Experimental results, using a programmable universal machine for assembly (PUMA) 560 arm, were reported. Many more researchers have studied the robotic loading problem for homogeneous materials, such as soils and regolith. The majority of researchers have advocated the use of manipulator impedance or compliant motion control [59.40–43] and much of this work has focused on estimating the properties of the media [59.44] and on computing the resistive forces acting on the bucket during loading [59.45].

Invariably, all researchers agree that the biggest challenge to robotic excavation is the interaction between the tool and the terrain (ground, pile). This interaction is shaped by the properties of the media (e.g., density and hardness), the rock pile geometry, and the distribution of particle sizes and shapes. The problem is compounded by the fact that it is difficult to predetermine the exact nature of interactions prior to the execution of any particular excavation operation [59.46]. Significant effort was dedicated to modeling the interaction between the bucket and the terrain in excavation. This requires estimating the soil parameters online, since these parameters can vary significantly with the strata being excavated. The classical fundamental equation of earthmoving [59.47] used to determine the forces required for digging will fail to predict these forces if the soil parameters are not estimated correctly. Models for automated excavation using online estimation of soil parameters are discussed in [59.48].

Situational awareness, which includes both workspace and machine awareness, is another key aspect of robotic digging. Workspace awareness implies a knowledge of the terrain surrounding the digging machine. At a primary level, this knowledge is gathered using a sensor suite retrofitted to the machine, which in a typical configuration consists of a number of ranging sensors, an inertial measurement unit, and a GNSS unit. The acquired raw data is subsequently processed by higher level processes to detect the location and configuration of the dig and dump regions, and the location of other mobile equipment operating the workspace (e.g., haul trucks, utility vehicles). Laser rangefinders offer adequate resolution to segment the scene. An example of a workspace image in a form of a three-dimensional (3-D) point cloud acquired with a long range laser scanner installed on a shovel is shown in Figure 59.5. Color is assigned to the points based on intensity returns from the laser scanner.

Machine self-awareness is primarily concerned with determining the position and orientation of the bucket

with respect to a referential fixed with respect to the machine. It also includes all the usual status data for the main onboard systems: power plant, transmission, tool actuation, etc.. The position and orientation of the bucket are usually available from encoders and inclinometers. A better solution, however, is to use suitably placed ranging sensors that are able to track the bucket in all positions and orientations [59.49]. This latter method avoids the errors typically associated with backlash in joints and dynamic effects in inclinometers. The placement of the ranging sensors on the machine should consider the need to provide an image of the ground under the boom.

Autonomous digging systems offer the additional benefit of enabling dig-to-plan operation and reconciling actual versus planned volumes by providing accurate real-time survey information. In surface mining operations, the floor is usually mined and therefore disturbed before accurate surveys are executed, and the floor is graded on an as-needed basis to facilitate the movement of the mobile equipment operating in the pit [59.49].

59.2.4 Robotic Dozing

Dozers are used in most surface mines. Operating a dozer under conditions that are dynamic, with hazards that can vary and be subtle and difficult to recognize, adds to the complexity of the tasks that workers perform on these machines. Many of these tasks require oper-

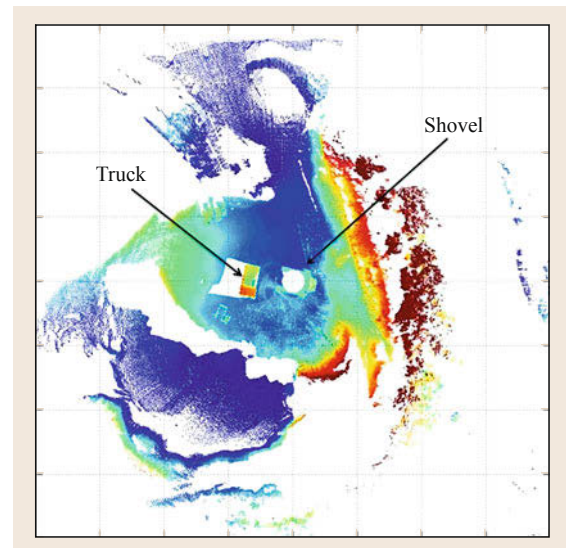


Fig. 59.5 A top view of a 3-D point cloud coloured by intensity returns from a long range laser scanner installed on a mining shovel loading a haul truck (courtesy of CSIRO, 2008)

ators that are highly skilled in ground-engaging tool control and machine positioning. In addition, dozer operators are exposed to a variety of risk factors that may lead to health problems, including whole-body vibrations, awkward postural requirements, noise, and shift work. While machine guidance systems are now ubiquitous, they still require an operator in the cab and have known problems associated with their reliance on GNSS-based localization. As alternatives, some equipment manufacturers offer tele-remote-controlled and autonomous dozers, which eliminate the need for an on-board operator.

Remote control solutions for dozers have been in use for two decades. They cannot perform in poor visibility conditions (dust, fog, night operation, heavy rain) and do not offer the possibility of automating machine guidance and tool control tasks otherwise available if operating the dozer from the cab. Other problems include loss of situational awareness, inaccurate attitude judgement, and inaccurate depth perception. More recent commercial remote control offerings include force feedback. In the case of tele-operated control with negligible latencies, imparting force feedback to the operator has the benefit of allowing the operator to *feel* and control the machine.

In view of the limitations of remote control technologies, research on dozer automation has focused on semi-autonomous and autonomous system retrofits. Autonomous systems have already made significant inroads in the mining industry, and the acceptance for this technology is growing. Leica Geosystems offers an autonomous ripping solution for track and wheel dozers. Their system, called Leica J³ dozer autorip, provides a number of automatic functions, which include engine start/stop engine, automatic control for steering, throttle, transmission and ripper, accessories control, and an emergency fail-safe system [59.50]. The system also incorporates a path planner based on area coverage algorithms.

59.2.5 Autonomous Blasthole Drilling

Blasthole drilling is a mining process typically employed during the exploitation phase of surface mining. To excavate a material it must first be blasted to fracture the rock mass into small volumes suitable for haulage and processing. This is achieved by drilling a matrix of holes from the surface down into the rock mass; these holes are then loaded with explosives and blasted. The resultant fractured rock mass can be excavated by a variety of machines. The matrix of holes (or *drill pattern*) and the amount and type of explosives used are optimized to produce a desired rock size distribution in order to minimize the cost of processing; however, there

can be significant variation due to the variable nature of the underlying geology.

Blasthole drill rigs are usually large tracked vehicles with an articulated *mast* that contains the main drilling components: the drill motor, drill rods, and drill bit. To drill to depths longer than the mast, drill rods can be concatenated to form a long *drill string* as drilling is progressing. Like many home drills, most blasthole drill rigs are capable of rotary drilling, as well as hammer (or percussion) drilling. Rotary is typically preferred for softer materials, with hammer drilling primarily used for harder materials.

There are several facets of drilling amenable to automation: tramming (the process of moving the entire rig from one hole location to another), drilling, and the management of drill consumables (such as rod or bit changes). A *fully autonomous* drill rig should have all of these functions automated. The promise of automation is increased productivity and more consistency in the placement and angle of drill holes, which in turn should lead to better blasting outcomes. Consistency in post-blast fragmentation results in a significant economic impact.

There are several high-profile mining equipment manufacturers and companies that have developed fully automated drill rigs. Atlas Copco's Rig Control System (RCS) has reportedly made significant impact in increasing average tramming speeds (from 0.8 m/min to 2.6 m/min) and drilling efficiency (a savings of 1 h per 12 holes drilled) [59.51]. Flanders [59.51], and Rio Tinto [59.52] also have fully automated blast hole drill rigs in production.

59.2.6 Telerobotic Rock Breaking

Drilling and blasting results are often far from ideal and the resulting fragments of rock (called *shot muck* or just *muck*) can be larger than the projected size. Some of the shot muck can be too big for handling with a digging machine, and thus requires a secondary blasting. Other boulders can be handled by the digging and hauling machines but are still too large to fit in the mouth of a primary crusher. In this latter case, rockbreakers are used to achieve a further reduction in ore and rock size.

A rockbreaker consists of a large 4-DOF (degree of freedom) serial link manipulator arm that is fitted with a hydraulic hammer (Fig. 59.6), and is usually positioned in front of a run-of-mine (ROM) bin. The bin is fitted with horizontal bars at the bottom that prevent oversized rocks from entering the crusher below (this arrangement is called a *grizzly*). The size of the grill openings is made in such a manner that only rocks small enough to be crushed may pass through. Larger rocks do not fit and therefore must be broken. Haul trucks car-

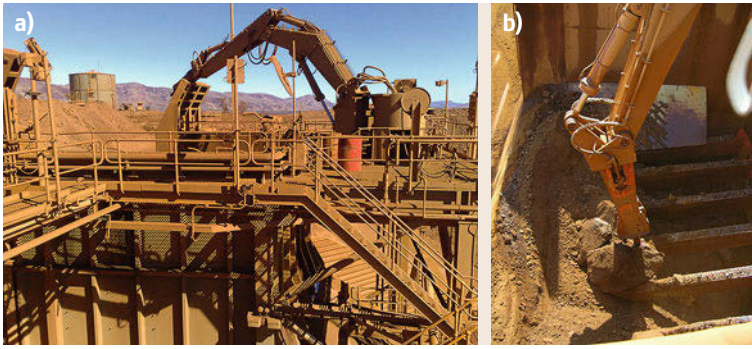


Fig.59.6a,b Rock breaker at rest over the ROM bin (a) and breaking a rock on grizzly (b) (courtesy of CSIRO, 2007)

rying ore from a nearby quarry dump their load into the ROM bin. Typically, an operator uses a line-of-sight remote control to operate the arm.

Rio Tinto is pursuing a programme to automate the vast majority of its Pilbara iron ore operations in Western Australia, and control the operations from the Remote Operations Centre (ROC) in Perth, situated over 1000 km away from the Pilbara region. This effort includes the development of a telerobotic control system for the primary rockbreaker at the West Angelas mine in collaboration with the CSIRO [59.53]. This system addresses known drawbacks in teleoperation (limited communication bandwidth, high latency in the real-time video feedback, lack of spatial situational awareness, etc.) by improving the intelligence of the control system at the remote/machine end (e.g., Cartesian motion and collision avoidance capability) and by providing the operator with a mixed-reality interface that combines live video with 3-D computer visualization.

Each rockbreaker is fitted with a number of sensors to detect its pose in space, and actuated by signals that bypass the existing remote-control system. PTU (pan, tilt, zoom) cameras are fitted to poles on either side of the ROM bin and a pair of high-resolution digital

stereo video cameras were mounted below. At the remote end, in the control room, the operator is presented with an overview of the rockbreaker from a wide-angle video stream augmented by a synthetic computer image (Fig. 59.7). The operator is able to *walk around* the rockbreaker in the virtual world and inspect the rocks from different angles, enabling the operator to determine the appropriate breaking strategy. The operator deploys the arm using commands from a joystick, and as the arm is commanded to move, the motion of the arm is replicated in the 3-D scene. Simultaneously, both PTZ cameras follow the tip of the hammer. When the operator is ready to break the rock, he/she can switch his/her attention to the live video stream, which can be used to monitor the breaking of the rock. Once complete, the arm can be automatically sent to the rest position.

59.2.7 Automated Loading Unit and Truck Interactions

The main loading units used in surface mining are electric and hydraulic shovels and hydraulic excavators. Given the large volumes of material that need to be moved, and the comparatively small size of loading and hauling units, cycle times are closely monitored. In the continuous pursuit of efficiency, mining engineers dissect cycles to look for potential savings. One area of interest is truck spotting, which is the process of manoeuvring the haul truck into a position and orientation that is ideal for the loading unit to dump material into the truck's tray (Fig. 59.4).

The ideal truck placement for loading has both productivity and safety implications. When a mining shovel is used for loading, the haul truck must be positioned in such a manner that the swing motion of the shovel is minimized and that the shovel boom does not need to lower excessively to reach the tray. If the haul truck is not placed optimally, the loader needs to reposition itself to tip with a full load in the bucket, which results in lost time. Lowering the loader arm excessively and/or an uneven distribution of load in the haul truck

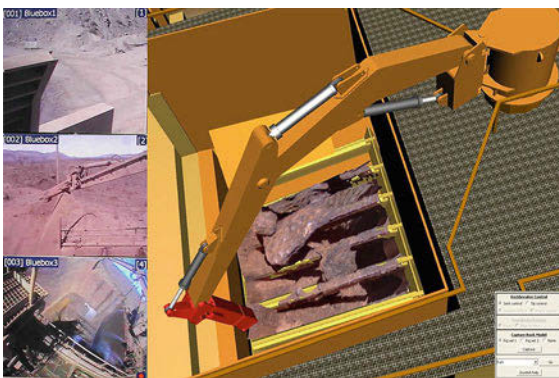


Fig. 59.7 A mixed reality user interface combines live video and 3-D stereo reconstruction of the rocks above the grizzly (courtesy of CSIRO, 2008)

tray may result in injuries to the operators and property damage.

In open-pit mining, the shovel operator usually guides the haul trucks to the desired location (spotting) by placing the bucket in the location that is optimal for the dumping phase, and waits for the truck to move into position. A key requirement for achieving automatic spotting is the availability of a robust localizer, that determines the relative pose between the shovel and the truck. Currently, most of the commercial guidance solutions are based on the use of GNSS and GNSS-aided inertial navigation systems on both the shovel and the truck. This results in an indirect determination of the relative pose between the shovel and the truck.

These systems, however, do not provide a robust solution. For the haul truck, the proximity to the shovel boom and crowd arm can lead to a degradation of the GNSS solution due to multipath, while the placement of the truck near highwalls leads to a partial obstruction of the sky, with a loss of satellite tracking and a significant geometric dilution of precision. The guidance system on the shovel can be impacted detrimentally by the proximity to highwalls. Imaging sensors (e.g., laser scanners) can be installed on both the shovel for a direct determination of the relative pose between the shovel and the truck [59.55]. However, this solution has potential pitfalls, that are related to the sensitivity of the imaging sensors to environmental conditions such as dust, rain, and variable illumination during the day (or during the 24 hour day/night cycle in cases where cameras are used).

Some researchers have looked at modalities that mitigate these pitfalls. One possible solution, suggested

in [59.54], is to divide the space around the shovel into three zones: the outer zone, the handover zone, and the work zone (Fig. 59.8).

The relative size of the zones depends on the truck and shovel geometries, and the chosen safe operating speed limits within each zone. As the truck crosses into the handover zone from the outer zone, the spotting system flags the truck as active and begins sending commands to it. In this zone, the relative pose between the shovel and truck is determined indirectly, based on the method discussed above. In the handover zone the truck is sufficiently far from the shovel and the highwall, and therefore the localization errors due to multipath and sky occlusion are minimized. Once the vehicle crosses into the work zone, the spotting system begins computing the relative pose using the imaging sensors on the shovel.

Since the sensors on the shovel are also able to see the bench and other obstacles in the work zone, the shovel is able to direct the truck around obstacles as they appear in the work zone, and park the trucks as close to the bench as practical. In other words, since the shovel is actively aware of its environment, it is able to deal with changes to the environment as they occur. The spotting system generates an approach path that will bring the truck in the optimum position for loading, where this optimum is determined in relation to the characteristics of the shovel and the configuration of the dig face. The path is also optimized with respect to the positioning time. Spotting times may be further minimized by double spotting, when the shovel loads on both sides, as depicted in Fig. 59.8.

The above discussion focused on shovel–truck interactions. Similar issues arise when hydraulic excavators are used for loading. Comprehensive research results in autonomous truck loading using hydraulic excavators are discussed in [59.56].

59.2.8 Dragline Automation

Mining *dragline* excavators are massive electrically powered machines used in open-pit coal mining to remove overburden and uncover coal. A dragline comprises a rotating platform that supports the house (consisting of the engine room and operator cabin), boom and a bucket rigging structure, as illustrated in Fig. 59.9. The house rotates on a base known as the tub which rests on the ground. The mechanism has three degrees of freedom:

1. Rotation with respect to the tub;
2. Hoist by a cable passing over sheaves at the tip of the boom;

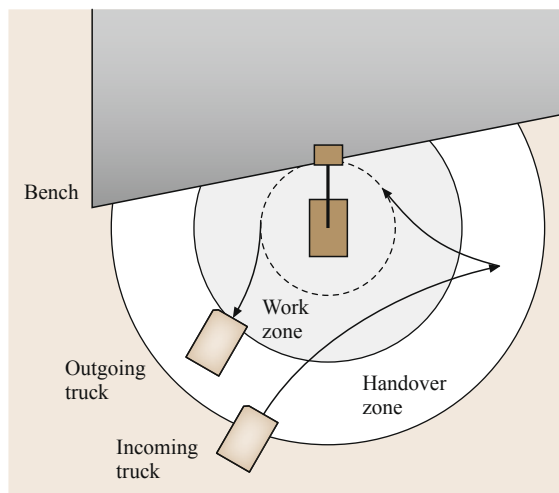


Fig. 59.8 Traffic management zones around a shovel in a double-spotting configuration, when the shovel loads on both sides (after [59.54])

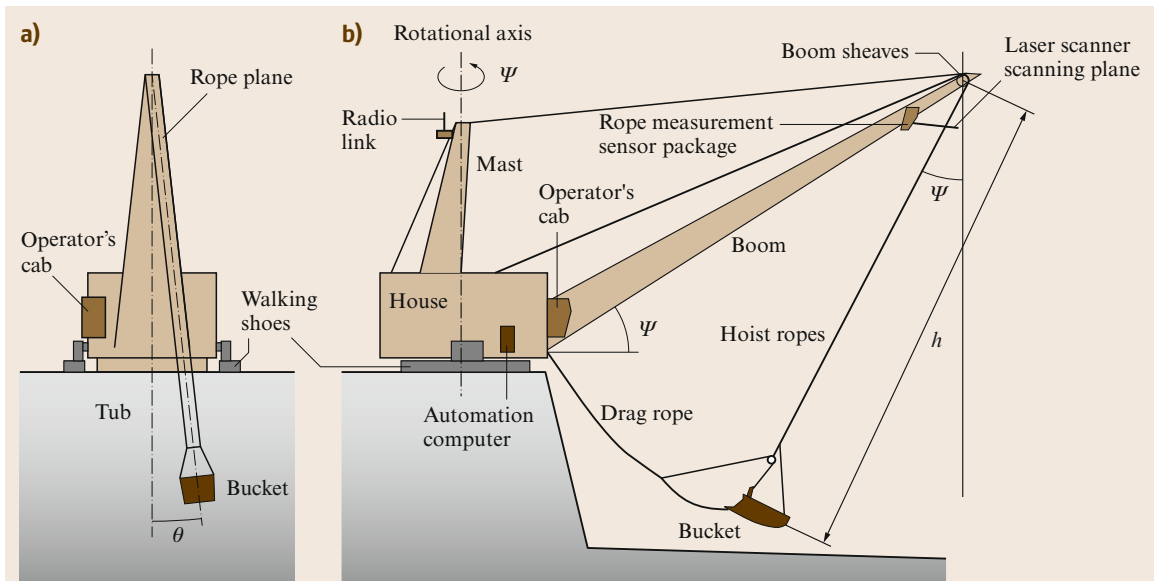


Fig. 59.9a,b Schematic of a dragline excavator (a) front view (b) side view (after [59.2])

3. Drag by a cable passing over sheaves at the base of the boom.

Digging is controlled using only the drag and hoist ropes. When the bucket is filled it is hoisted clear of the ground and swung to the dump position by swinging the house and boom. The human operator fills the bucket by dragging it through the ground, lifts and swings it to the spoil pile, dumps it, and then returns to the dig point. Each cycle moves up to 100 t of overburden, and typically takes 60 s.

High capital costs are pushing the owners of these machines to continually look for avenues to maximize productivity (m^3/shift) in the presence of operator variability and maintenance costs (around 30% of operating cost) [59.2]. From this perspective, dragline operations seem ripe for deploying robotic technologies. However, the idea of completely removing the human operator from the dragline seat, while tempting from a research perspective, it is not widely entertained in the industry.

Swing control and digital terrain mapping are the two robotic technologies at the core of the dragline automation efforts. During dragline operation, the bucket naturally tends to swing with respect to the boom. A skilled operator can coordinate the boom slew motion so as to control the natural tendency of the bucket to swing during dumping and spotting operations. A novice operator typically requires six months training to become proficient. This warrants the development of a swing automation system to improve the productivity of the dig-to-dump and dump-to-dig phases of

a dragline operation. Automatic swing controllers offer the additional benefit of minimizing stress fatigue on the boom.

An implementation of a dragline swing controller is discussed in [59.57]. The control system moves the bucket between operator-specified dig, and dump points, passing through intermediate (via) points. The rather rigid programming of control (dig, via, and dump) points has a number of disadvantages. Firstly, as the spoil pile grows the dump point must be raised. If the automation system does not contain a model of spoil growth, the operator has to make adjustments by retraining the system, resulting in time losses. Secondly, if the operator does not correctly identify a via point at a critical area, such as the top of the high wall, the swing automation system will not know the high-wall is there and may attempt to swing the bucket through it. Augmenting the automation system with a digital terrain mapping capability provides a common solution to these problems.

One implementation of a digital terrain mapping solution for draglines is described in [59.58]. Maps were created using data from a real-time kinematic (RTK) GNSS system and a two-dimensional (2-D) laser scanner. The laser scanner was mounted at boom tip in such a way that the scanning plane intersected the ground underneath the boom, and tilted by about 7° with respect to the vertical. Tilting the laser minimizes the likelihood of the bucket and ropes blocking the laser's view. The terrain is scanned as the dragline swings during the normal operation cycle, a typical map is shown in Fig. 59.10.

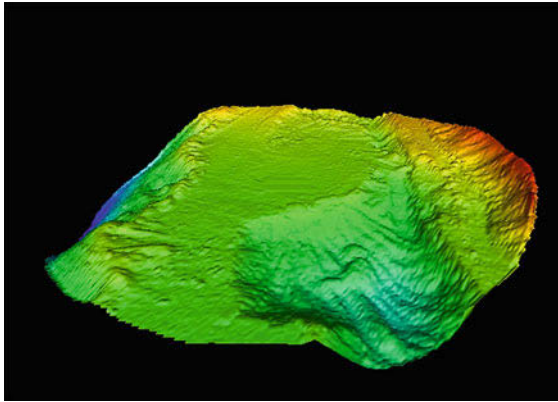


Fig. 59.10 Image of a digital terrain map created from a long range laser scanner installed at the tip of a boom dragline (courtesy of [CSIRO](#), 2005)

The implementation of a digital terrain mapping function in dragline automation systems also enables the measurement of dragline productivity in real time. Commercial dragline monitoring systems can only measure the approximate weight of each bucket, and the approximate disengage and dump points. They cannot provide indications of where the where the spoil is located in relation to the dragline, of the actual volume of overburden moved, or how much re-handle took place [59.58].

59.2.9 Machine Positioning and Terrain Mapping

The task of establishing and maintaining the vehicle positioning (i.e., position and orientation) relative to an external frame of reference is a fundamental problem in autonomous vehicle navigation and control, and this hold true for mining applications. High-accuracy positioning technology is a dynamic area of research and development, spurred on by the advances in satellite positioning as well as by the current challenges for the technology in mining systems, especially in surface mining operations. The following initiatives are underway to improve the availability and robustness of current technologies, which have and will further enable the application of robotics in surface mining:

- Public GNSS systems (e.g., [GPS](#) and [GLS](#) (global navigation satellite system))
- Augmented public GNSS systems (e.g., [GPS](#) with [WAAS](#) (wide area augmentation system))
- Locally augmented GNSS systems (e.g., [DGPS](#) (differential global positioning system) or [RTK GPS](#))

- Pseudolite augmented GNSS systems (i.e., through the installation of Earth-based transceivers)
- Closed systems (i.e., wholly proprietary systems relying on a constellation of locally installed Earth-based pseudolites).

For example, in the mining domain, Leica Geosystems offers the Jigsaw Positioning System ([JPS](#)), a product that offers a significant breakthrough in addressing the major shortcomings of GNSS [59.59]. Based on a technology developed by the Locata Corporation [59.60], [JPS](#) is a ground-based network for positioning that in principle mirrors the functionality of GNSS. It circumvents the fallacies of GNSS by using a terrestrial network of transmitters that can be placed in optimal locations with respect to the mobiles being tracked.

Different from pseudolites, an example of technology for positioning in GNSS-denied environments is [CSIRO](#)'s wireless ad-hoc system for positioning ([WASP](#)) wireless tracking technology. The system can be configured as a mesh network and offers a unique combination of high accuracy, high resistance to multipath interference, low-cost hardware, and ability to be rapidly deployed [59.61]. The accuracy of [WASP](#) depends upon the radio propagation environment, and is typically better than 0.25 m under line-of-sight conditions, even in the presence of substantial multipath interference. The maximum range over which [WASP](#) nodes can measure range and communicate is typically over 400 m, and can exceed 1 km. As [WASP](#) can form a mesh network, the overall network size is not limited. The maximum location update rate is 200 Hz; however, there is a tradeoff between the number of nodes and update rate, and a typical update rate is 1–10 Hz.

Terrain Mapping and Surveying

The penetration of robotic and autonomous systems in mining, coupled with new computer aided tools for mine modeling and reconciliation, requires more accurate and timely information about the current state of the mine, and at higher spatial and temporal resolutions. In the traditional surveying framework, one obvious solution is to increase the number of surveys (reduce the time gap between successive surveys) and the density of survey points, while reducing the costs per survey. To address this, a number of vehicle-based scanning systems have been recently introduced to the market. The mode of operation ranges from stop-and-go-type systems (such as the Maptek I-Site), to continuous scanning mobile systems, such as those offered by Riegl (VMX 250), Topcon (IP-S2), and Trimble (MX-8). In general, these systems integrate high-end [LIDAR](#) (light detection and ranging) with GNSS-aided [INS](#) (inertial

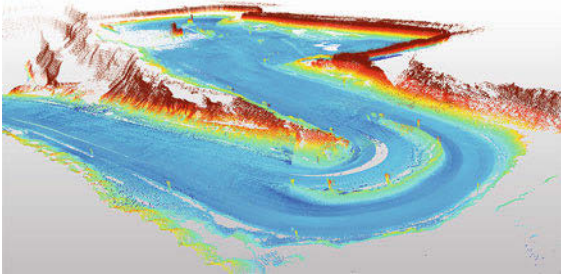


Fig. 59.11 A 3-D map of a surface mine created from a mobile mapping system installed on a four wheel drive (4WD) vehicle (courtesy of CSIRO, 2012)

navigation system) and carry a significant price tag, which can limit deployment to a single dedicated survey vehicle.

On the other hand, consider the application of simultaneous localization and mapping (SLAM) in mining. SLAM is a mature area in mobile robotics and efforts are underway to transfer the technology to mining. Data-fusion techniques used in SLAM make it possible to use lower cost mapping sensors, which in turn enables mining companies to deploy the equipment on a multitude of utility vehicles and/or heavy-duty mining equipment (Fig. 59.11). As a result, the vast majority of survey work can be performed during the normal operation of the equipment in pits, on haul roads, or other site areas, without directly exposing surveying personnel to the perils of conducting survey work in high-risk areas.

59.2.10 Mine Safety

The increase in demand for resources has posed new challenges to increase productivity, while at the same



Fig. 59.12 Complexity of mining equipment interactions affected by adverse environmental conditions (courtesy of CSIRO, 2012)

time continually improving the standard of safety. Robotics is beginning to play a role in this. There are inherent risks associated with manually operating vehicles in mining environments. Operators work long shifts and the view from the driver's cabin can be very restricted. Furthermore, vehicle interactions are inherently difficult due to the size of machines, and can be further complicated by environmental conditions such as dust, fog, and snow (Fig. 59.12).

Each year there are hundreds of mine haulage accidents that result in significant numbers of injuries, even deaths, and large financial costs due to machine downtime and repair of equipment. According to the United States Mine Safety and Health Administration (MSHA) [59.62], from 2002 to 2008 the United States coal industry alone averaged 1206 accidents per year involving mobile equipment.

During the past few years, a number of approaches have been introduced to assist operators in becoming more aware of safety risks in the local environment. These technologies and methods include proximity awareness technology (PAT), proximity detection technology (PDT) and collision avoidance technology (CAT). It is important to note that, in surface mining, these existing technologies do not perform any control action. They merely provide information to the driver, who remains in total control of the vehicle.

Detection of Threats

In general, most safety incidents are from vehicle interactions with other vehicles, fixed infrastructure, or personnel. A large proportion of these incidents happen at low speed. This is most likely to occur on vehicle startup, or at the loading areas with interactions between trucks, shovels, loaders, and other ancillary equipment. These accidents are usually of low impact but can cause serious damage to equipment and significant loss of production.

The fundamental approach to reducing the likelihood of low-speed incidents is to provide the operator of large vehicles with aids to see into blind areas such as side or back of the vehicle. These aids are normally based on standard video or infrared cameras. The next level of risk reduction is achieved by incorporating automatic detection of resources and people in close proximity by utilizing range and bearing sensors. Radar is a preferred sensor modality for bad environmental conditions. Wide beam radars are very common but they are prone to false alarm. New recent developments mitigate this problem by using electronic-mechanical scanning narrow beam radar technology [59.63, 64].

High-speed incidents occur less frequently than at low speed, but often result in serious injuries and fatal-

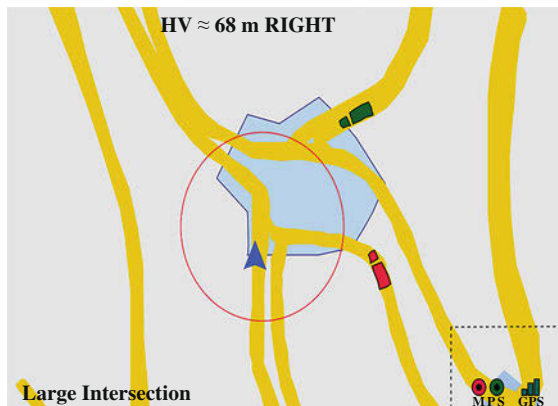


Fig. 59.13 Graphical representation of the state of the world close to the vehicle, including other vehicles in proximity, maximum risk, most likely paths, and risk areas (context) (courtesy of Eduardo Nebot, 2011)

ities. The time available to stop the vehicle or perform an evasive maneuver is reduced and consequently long-range detection of threats is necessary in order to take early preventive action.

This is addressed by incorporating vehicle-to-vehicle (V2V) communication with all nearby vehicles at sufficient range to provide early warning of potential threats. V2V networks can also form a mesh structure. The fundamental advantage of this approach is that no fixed infrastructure is required, and communication between vehicles can be guaranteed anywhere in the site when vehicles are in radio range.

Positioning, Context, and Road Maps

Positioning is one of the fundamental components of a comprehensive safety system. The incorporation of

GNSS systems, integrated with velocity and inertial observations, allows for the evaluation of reliable time-to-collision (TTC), especially when combined with haulage road maps information.

Determining the risk of a situation is entirely dependent on the context of the situation. One important situation context is the location, or more specifically the type of area the vehicle is currently operating. The expected behavior and driver intent [59.65, 66] varies depending on whether they are driving on a road, parking in a designated area, or dumping ore in a crusher. Map information is required to allow the system to vary the information provided to the operator depending on the location. An example is shown in Fig. 59.13, where the map allows the operator to become aware of the risks, and complexity of the situation, independent of the weather or geometry of the terrain.

Monitoring and Design

The ultimate goal of any safety system is to find a complete solution to the safety problem by introducing new technology, methods, and algorithms. It is very unlikely that this can be achieved with a single technology alone, perhaps with the exception of a fully autonomous system implementation. An active area of research and development aims to use both reactive and proactive approaches to solve the safety problem. At the reactive level, technology is used to assist the operator in recognizing and avoiding the safety risks. At the proactive level, managers are provided with tools to monitor, analyze, design, and improve the safety of the mining operation. This new comprehensive approach to safety has the potential to eliminate all accidents in the mine by integrating technology, procedures and intelligent algorithms to make the mine safer and more productive.

59.3 Underground Mining

The especially hazardous and generally unpleasant nature of underground mining environments, operator safety and fatigue, labor costs, and the repetitive nature of the ubiquitous load-haul-dump cycle all motivate autonomous and semi-autonomous and teleoperation-based solutions for underground machines and processes.

59.3.1 Telerobotic Operations

In mining, *remote control* typically refers to the control of a machine where the operator has a direct line-of-sight view of the machine. Remote control is normally used only for excavation (or *mucking*), not for driving

(or *tramming*) of loaders, for instance. Remote control systems are widely used, for example, when loaders must access underground drawpoints where there is a risk of falling ground.

By remotely operating equipment or through the partially autonomous operation of equipment, for example, it stands to reason that the exposure of personnel to unsafe circumstances might be significantly reduced. This was argued to be true at Inco Ltd. during the 1990s [59.67].

Telerobotic systems are those in which a human remains part of the control loop, although *at a distance* and not generally within direct view of the system being controlled. Many mining companies and equipment

manufacturers are now finding benefit in the application of telerobotics, particularly to underground equipment such as LHD machines (Fig. 59.1b) and drills [59.67–69]. This is normally done by the real-time transmission of video and control signals to and from a remote control room; Figure 59.14, which shows a commercial teleoperation station.

However, teleoperated equipment may not be as productive as manually operated equipment, for example, due to visibility and issues related to reduced operator feedback. Recently, some researchers have proposed the development of semi-autonomous teleoperation systems, whereby the operator's actions are filtered by a machine control system that regulates operator commands with some degree of partial or *local autonomy* [59.70].

59.3.2 Autonomous Tramming

Autonomous *tramming* refers to automating the driving task of underground mining vehicles, which is often a repetitive activity. Most robotic tramming systems have been developed for LHD machines, such as the one shown in Fig. 59.1b, although some suppliers also have systems available for their underground haul trucks.

Several challenges exist that make the autonomous tramming problem difficult. For example, the large inertia of these vehicles and their hydraulically actuated, center-articulated steering mechanisms make them difficult to control at high speeds. Another is the problem of precise and real-time underground localization in the absence of global infrastructure (most notably, GNSS available on the surface).

Underground Navigation

Early autonomous tramming systems worked by outfitting the mine with signal-emitting cables [59.71],



Fig. 59.14 Teleoperator's station for control of underground robotic vehicles at the Kemi mine, Finland (courtesy of Atlas Copco, 2009)

reflective strips [59.72], light-emitting ropes [59.73], or reflective tape [59.74, 75]. Other systems required beacons, placed at strategic locations throughout the mine, which allowed the vehicle to estimate its position by measuring angles to the beacons and comparing the measured angles to those expected from a map of known beacon locations [59.76].

One drawback to these early systems is the time-consuming task of installing, localizing, and maintaining the necessary infrastructure, particularly as the mine advances. To the best of our knowledge, none of these systems ever saw widespread use in industry. The state of the art in underground autonomous vehicle systems is infrastructureless.

One of the first infrastructureless technologies was one initially developed by an Inco Ltd. spin off. The patent [59.77] describes the use of a map consisting of a set of interlinking nodes intended to represent the topology of the underground passageway environment. The nodes themselves are located at points of interest, such as at intersections, dead ends, etc. Thus, a topological map was used for navigation, which relied on an algorithm capable of classifying all of the possible tunnel geometries encountered in the mine. Steering the vehicle was then done by a lower-level reactive algorithm, which tried to keep the machine near the tunnel center. A range-sensing device was used to sense the distance to walls.

This topological and reactive approach to underground navigation and control was tried again after [59.77]; see also [59.78–81]. Recently, these methods have also been combined with radio frequency identification (RFID) tags to provide a global reference [59.82]. This general approach is what formed the basis for one of the first truly commercial autonomous LHD systems, which is now offered as a product by Caterpillar Inc. (see the following). However, the main drawback to this technology is that it relies on classifying tunnel and intersection topology. As roboticists know, misclassifications can happen in practice.

Inspired by advances in mobile robotics research, some considered the application of alternative map-based localization algorithms – the idea being to match sensor measurements to a map rather than by classifying tunnel topology [59.83, 84]. In most cases, a planar poly-line representation of the mine was used to help the vehicle navigate. This is the approach taken by Sandvik AB in their commercial offering. More recently, Atlas Copco Rock Drills AB entered the underground automation game by applying an approach similar in philosophy, which generates sequences of occupancy grid maps and subsequently uses these to estimate the vehicle's position in real time by way of an

unscented Kalman filter (UKF)-based algorithm [59.85, 86].

Vehicle Control

A machine control system capable of performing at or better than a human operator is necessary in order for robotic tramming systems to compete in industry with manual operation. Many researchers have proposed articulated vehicle steering controllers based solely on vehicle kinematics [59.87–90], while few have considered dynamics [59.91]. Others have contended that wheel slip is significant and should be explicitly accounted for [59.92]. The paper [59.86] describes a control architecture and implementation that permits high-speed tramming by handling hydraulic vehicle steering and driveline dynamics by explicitly forcing a bandwidth separation between low-level machine/actuator dynamics and the path-tracking control problem, which is solved at the kinematic level.

Commercial Products

Although product descriptions are not the primary focus of this chapter, it is worth briefly mentioning that there are (at the time of writing) three main commercially available underground vehicle automation products: Caterpillar MineStar system for underground [59.93], Sandvik AutoMine [59.94], and the Atlas Copco ST14 ARV [59.85] (VIDEO 142).

Mobile equipment vendors, not third-party suppliers, sell all three. All three systems are infrastructure free. They all operate by scanning the vehicle's local environment with a 2-D SICK laser rangefinder and combining this data with wheel encoder information. All three systems operate in conjunction with a high-

speed wireless network. What is more also all perform autonomous dumping. A schematic of the Atlas Copco product is shown in Fig. 59.15, highlighting the sensor and control components used for robotic tramming.

59.3.3 Robotic Loading

Despite a significant amount of research effort in the field of robotic excavation, none has yet resulted in the widespread development or adoption of autonomous or semi-autonomous excavation technologies in the mining industry. Although this section focuses on loading from an underground mining perspective, robotic loading is also applicable to surface mining operations (Sect. 59.2.3).

Robotic excavation is especially challenging because of the dynamic and unpredictable nature of the bucket-rock interactions. Also, a dig controller must manage not only the motion of the excavation arms (e.g., boom and bucket links), but also the penetration rate as determined by the motion of the mobile platform. As a result, performance is highly influenced by the conditions of interaction between the machine and its environment. For example, the forces that act on a bucket as it is actuated to penetrate a rock pile may vary significantly depending upon the properties of the media (e.g., density and hardness), the rock pile geometry, and the distribution of particle sizes and shapes [59.95, p. 562].

It is important to distinguish between excavation in homogeneous materials, such as soil, sand, or regolith, and the challenge of excavating fragmented rock as in mining, which usually has a significant distribution of particle sizes. Fragmented rock may consist of both *finer* (i.e., very small particle

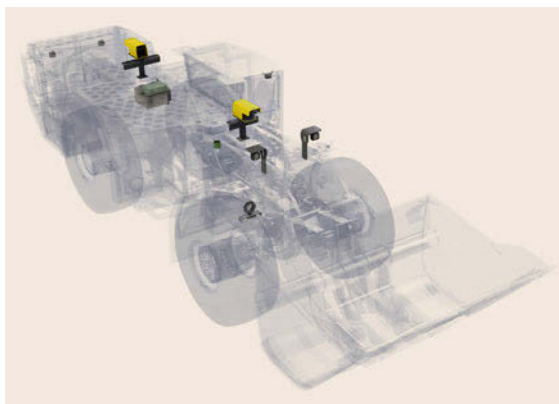


Fig. 59.15 Scooptram (or LHD) components for robotic tramming, including SICK scanning laser rangefinders (front and rear), articulation angle encoder, drive shaft encoder, onboard cameras, and computing subsystems (courtesy of Atlas Copco, 2009)



Fig. 59.16 EJC 9T LHD machine conducting robotic excavation experiments in fragmented rock at the engineering facilities of Sandvik Mining and Construction Canada, Burlington, Ontario (courtesy of Joshua Marshall, 2000)

cles), *oversize* (i.e., particles too large for the excavation tool), and a range of sizes in between. Figure 59.16 shows an EJC 9T LHD machine conducting robotic digging experiments in fragmented rock.

The robotic loading problem can be split into two fundamental tasks [59.96]:

1. Dig planning
2. Dig execution and control.

Dig planning constitutes the problem of deciding where and what to dig, possibly considering the geometry of the rock pile, the distribution of particles, and the physical characteristics of the loader and bucket. Dig control refers to algorithms for modifying plans based on the nature of the media encountered, so as to efficiently fill the loader's bucket. This task of the problem is particularly challenging in fragmented rock.

Dig Planning

Machine vision has been proposed as an enabling technology for dig planning. The paper [59.97] describes a laboratory-scale excavation system that utilized camera data for control and navigation. In [59.98], a scale-model system was built to mimic the motions of an LHD and different loading strategies were developed that depend on sensed information about the rock pile. Similar work, described in [59.99], employed a vision system to obtain images of the rock pile. In their approach, these images were used to plan the excavation task based on an estimated contour of the rock pile. In more recent work, the authors of [59.100] conducted an experimental study of two novel approaches for selecting an attack pose from 3-D data, with the objective of eventually using this for the robotic loading of sand.

Dig Execution and Control

The dig execution and control tasks have been tackled by several robotics researchers during the past two decades. Much of this work has targeted surface mining applications (Sect 59.2.3), although some concepts are transferrable to underground. Targeting underground, in [59.101] it was suggested that the trajectory of an excavator's bucket through the rock pile should not have priority in a devised control scheme, since the objective is to effectively fill the bucket, not to follow a predetermined path. This was explored further in [59.46, 95], which proposed an algorithm for robotic digging that would respond to bucket-rock interaction forces sensed as changing pressures the excavators bucket cylinder by commanding a change in the cylinders retraction velocity, rather than its position. This strategy was based

on full-scale experiments with an LHD. Together with Atlas Copco AB, researchers at Queen's University in Kingston, Canada have recently demonstrated this admittance-based robotic loading strategy by way of full-scale experiments on a modified Kubota loader (on surface) and an ST14 LHD (underground), as shown in VIDEO 718.

59.3.4 Longwall Automation

Longwall mining is one of the main extraction methods for underground coal mining. This method is highly efficient in cases where thick seam reserves are present, with high-quality coal at shallow depth and benign geological conditions [59.102]. In the longwall process, a *shearer* – a machine with large rotating cutting drums – is driven back and forth across the seam, with each pass taking a massive slice of coal.

Figure 59.17 shows a schematic representation of a longwall mining equipment installation. Two long, horizontal and permanent tunnels known as *gate roads* are cut into a coal seam to form the main boundaries for a large rectangular block of coal, known as a longwall panel. The shearer travels in this panel along the face on a structure also housing an armored (or articulated) face conveyor (AFC) that carries the coal to one end of the face. The coal is then removed via other conveying systems to the surface. The roof is supported over this operation by a number of adjacent powered roof supports (also known as *shields* or *chocks*) which are each connected to the AFC. After the shearer passes, the chocks release from the roof, advance under hydraulic power into the cavity created by the removal of the coal, reposition the AFC, and re-support the roof [59.2].

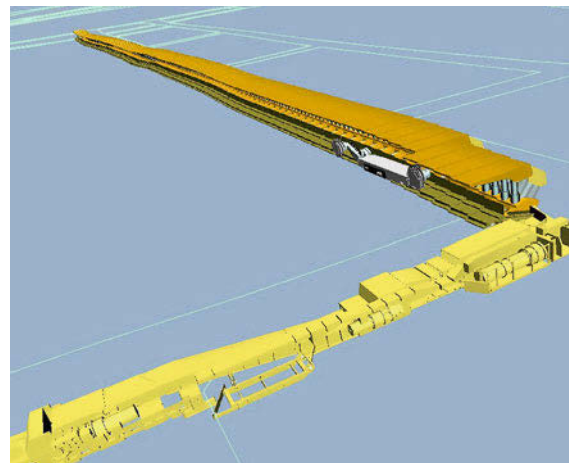


Fig. 59.17 Schematic of a longwall mining equipment installation (courtesy of CSIRO, 2008)

A concerted effort to deliver automation solutions for longwall mining saw the establishment of the Longwall Automation Steering Committee (LASC) in 2000, comprising Australian Coal Association Research Program (ACARP) industry representatives, equipment manufacturers, research providers and mine safety authorities. With funding from ACARP, CSIRO and the Cooperative Research Centre for Mining Technology and Equipment (CMTE), now CRC Mining, embarked in a major project to deliver automation solutions for coal cutting and loading, maintaining face geometry and manipulating roof supports without human intervention.

Three issues were identified as critical for longwall automation [59.103]: Face alignment, horizon control, and creep control. Until recently, efforts to develop automatic controllers for face alignment were hindered by the lack of an automatic and reliable method for measuring the actual geometric profile of the longwall face. The solution provided in this project employed a high-end inertial navigation system to provide accurate shearer position and attitude information in real time. The system is shearer-mounted and is referred to as the Shearer Position Measurement System (SPMS). One of the major outcomes of this project was the development of open specifications for the SPMS, and as a direct result, all the major longwall equipment manufacturers now offer automatic face alignment systems.

The second significant technological challenge tackled by LASC was achieving enhanced horizon control (EHC). While face alignment occurs in the horizontal plane, horizon control occurs in the vertical plane, and is significantly more difficult. In order to maximize the extraction of coal and minimize the extraction of waste, the roof and floor cutting horizons need to stay within the coal seam. The EHC incorporates two independent horizon controllers: one for the floor and one for the roof. The set points for the two controllers are generated by an integrated cut model, which sits at the core of the EHC. The cut model incorporates real-time information from navigation sensors, coal interface detectors, seam tracking sensors, as well as off-line geological and geotechnical information.

Finally, *creep control* refers to maintaining the lateral position of the longwall equipment in the panel. As the longwall mining system progresses, the assembly of supports should not creep toward either of the two gate roads. The LASC solution measures creep using laser range finders that scan in a horizontal plane in the panel and roadway directions. The creep information is provided to the longwall shearer automation processing system and generates corrections in the face

profile in the form of a lead to either of the gate ends [59.103].

59.3.5 Robotic Explosives Loading

Many tasks in mining and construction require the driving of horizontal and inclined tunnels (or *drifts*) by drilling and blasting for rock fragmentation. Currently, drilling and blasting also remains the primary method for recovering ore from blocks (or *stopes*) in underground hard-rock mining. Blasting engineers design a blast hole pattern that specifies the size and location of the holes in order to achieve the desired rock fragmentation and minimize the damage to the rock mass left behind.

Blast hole charging is a two-step operation. In the first step, the operator places a primer assembly at the end of a flexible hose, inserts the hose into the blast hole, and pushes the hose until the primer reaches the end of the hole. A *primer* is a compact device containing high strength, sensitive explosives used to safely initiate the main column in the blast hole at a controlled time provided by the detonator. Initiation requires electric energy, usually delivered by detonating cords. The hole pushing is mechanized. In step two, an explosive emulsion is pumped into the hole through a hose, the hose is retracted as the explosive gradually fills the hole, leaving the trailing detonator wire. Once a ring of blast holes is filled, the detonator wires are joined and the rock is blasted.

A robotic explosive charging system (RECS) developed by the CSIRO [59.104] incorporates technologies that make the operation of loading holes safer with comparable or better productivity than otherwise possible. The system incorporates mixed teleoperation and robotic capabilities that allow the operator to load the entire pattern from the comfort and safety of the cab of the loading truck. The prototype RECS was developed for a mechanical manipulator derived from a Palfinger truck crane. The system is able to locate blast holes using the laser rangefinder attached to the arm end effector. An automatic arm pose control function is used to achieve a sweeping motion of the arm, during which the laser rangefinder collects images of the tunnel. These images are subsequently processed to extract blast hole locations, and presented to the operator via a human-machine interface.

Once the holes are identified in the scan, they are matched with the holes present in the blast plan and the operator is ready to proceed with the charging. The robot arm is sequenced to pick up the primer assembly from a magazine, and transfers it to the hole. The primer ends up at a pre-set offset from the

hole collar. In teleoperation mode the operator uses in-cab joysticks to insert the primer and the hose in the hole. The video system provides the operator with real-time video images of the relative positioning between the tip of the end effector and the blast hole collar.

In the work of [59.104], hole identification was carried out for 89 and 102 mm blast holes. While the hole diameter is used as a parameter in the identification algorithm, determining the hole length was not a requirement (this is not to say that in-situ validation of drilled versus planned is not important). During scanning, the robotic arm moves the end effector back and forth through the tunnel. The end effector is sequentially rotated, such that the laser is capable of scanning a full 360° pattern in the tunnel. Successful hole detection is influenced by the relative alignment between the laser beam and the hole axis. The larger the misalignment, the greater the chance of generating a false negative. Figure 59.18 shows a typical 3-D profile used for hole identification.

Visual servoing requires locating the tool in relation to the target hole. Cameras mounted on the end effector provide estimates of the location of blast holes with respect to the end effector. The control methodology does not require extensive knowledge of the manipulator physical parameters, and uses a minimal set of tuning parameters, to allow operators to make adjustments if and when required. However, finding an adequate solution raises a number of significant challenges when using a typical truck crane as a robotic arm.

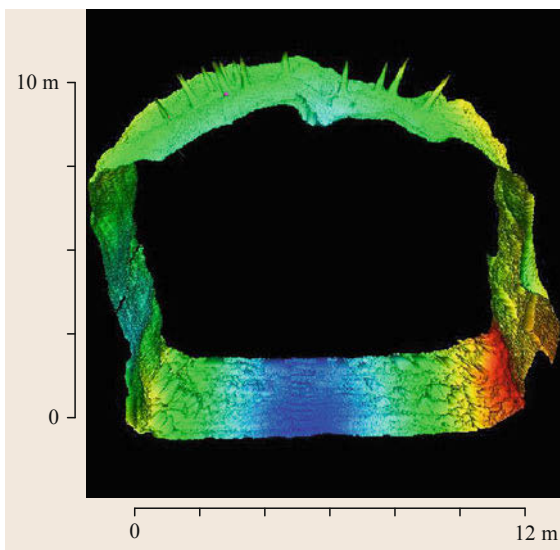


Fig. 59.18 A 3-D tunnel profile generated for identifying blast holes in a tunnel (courtesy of CSIRO, 2006)

59.3.6 Underground Mapping, Surveying, and Positioning

Mapping, surveying, and real-time equipment positioning are core services in many industries, and mining is no exception. In surface mining, the advent of the satellite-based **GPS** in the 1980s led to fundamental changes in the way everyday operations are carried out [59.105], with new applications being developed even more recently (Sect. 59.2). Based on GNSS, accurate site surveys, information systems, and robotic tools that enhance safety, improve productivity, and cost-saving maintenance operations, for example, have become commonplace in surface mining [59.1, 106].

However, similar progress has been made more slowly in underground mining because no directly comparable positioning technology currently exists for the accurate and real-time localization of mobile equipment in underground mining operations. This section discusses some tools and techniques from the field of robotics that have found their way into mining for such purposes as surveying, mapping, and equipment localization.

Underground Mapping and Surveying

At present, manually generated survey maps in mining are used for the design and construction of structures, ventilation, power, drainage, haulage planning, and tracking of development and ore extraction progress [59.107]. However, traditional surveying techniques are slow and laborious, involving many manual steps, infrastructure installation (e.g., retroreflective markers), and repeated measurements to obtain the necessary accuracy for the given application. Conventional survey maps are invariably a coarse approximation of the actual mine structure because, while individual observations may be accurate, few measurements are taken (i.e., poor resolution). Also, surveying is a regulated practice; thus the use of new techniques from robotics requires that current standards be updated.

Several recent advances out of the robotic mapping community show promise for applications in underground mining, and we mention just a select few here as examples. Authors from Carnegie Mellon University (CMU) [59.108, 109] describe robotic systems developed for acquiring volumetric maps of underground mine workings; specifically abandoned mines where ground conditions may be hazardous. **SLAM** results, based on data from 2-D scanning laser rangefinders, were reported from data obtained in two mines: a research mine in Bruceton, PA, and an abandoned coal mine in Burgettstown, PA.



Fig. 59.19 3-D SLAM-generated map of a decline at the Northparkes mine (after [59.112]); the gaps on the floor and ceiling are due to the blindspot between two vertically oriented SICK laser rangefinders; electrical cables can be seen along the left side wall (courtesy of So Jung Yun, 2012)

Some have developed techniques for robotic exploration and topological mapping [59.110] by focusing on the detection and matching of underground mine tunnel intersections as a basis for the creation of topological maps.

New scan registration techniques, such as 3-D-NDT (three-dimensional normal distributions transform) [59.111], have also been conceived specifically for underground mine mapping. Authors from the AASS in Sweden compared their results with the popular iterative closest point (ICP) algorithm on actual mine data.

Recently, researchers at CSIRO [59.112] demonstrated a 3-D SLAM solution, consisting of a spinning 2-D scanning laser rangefinder and industrial-grade micro-electromechanical system (MEMS) inertial measurement unit (IMU). The system was mounted on a site vehicle at the Northparkes mine (Parkes, NSW) that continuously acquired data at typical mine driving speeds. The deployed system mapped over 17 km of mine tunnels in under two hours, resulting in a dense and accurate geo-referenced 3-D surface model. Figure 59.19 shows an example of the generated surface model.

Underground Positioning and Tracking

The satellite-based GPS uses radio frequency signals that cannot usefully penetrate significant obstacles (e.g., rock); see any reference on the fundamentals of GPS [59.113, 114]. Although high-sensitivity receivers are being developed [59.114], these will almost certainly not function underground. For buildings, some have proposed the use of signal repeaters [59.115], but this is again not practical for most underground mine environments. These challenges necessitate a different approach for underground mines.

As a result, several alternatives for underground mining have appeared in recent years, many of which have limited functionality or are, as of yet, unproven. A recent summary, found in [59.116], presents a survey of the most commonly cited approaches:

- Employing RFID tags for event-based tracking of equipment and personnel [59.117].
- Use of radio signals (e.g., installed Wi-Fi access points) for signal strength-based positioning [59.118, 119], which is very difficult in underground mines due to severe multipath and shadowing, as well as non-line-of-sight propagation and the need for too many devices in order to obtain GPS-like accuracies.
- Dead reckoning using inertial sensors (e.g., IMUs) and odometry for only short-term machine tracking.
- Rock-penetrating very low frequency electromagnetic signals, generally limited to near surface (< 200 m) [59.120] with questionable accuracy [59.121].

However, none of these options yet offer a solution comparable to that provided by GNSS on surface. Another issue is that mining practitioners often do not appreciate the technical limitations of these approaches [59.116, 122]. As a result, some have recently proposed the adaptation of map-based localization techniques for underground mining equipment. For example, [59.123] describes a method for large-scale mapping that employs a combination of RFID tags (as landmarks) and occupancy grid mapping specifically designed to facilitate real-time underground vehicle localization.

59.4 Challenges and Industry Acceptance

Despite the latest uptake of robotics technologies in mining, significant challenges remain. Next, we briefly review the most significant ones that are likely to affect the diffusion rate of autonomous systems in mining.

59.4.1 Technological Challenges

One expression that describes the current situation of robotics in mining is *islands of automation*. This re-

flects the significant integration issues that exist in relation to fully autonomous and mixed autonomous-manual/remote equipment. The root cause of the problem is a lack of standards to which the various equipment manufacturers should align. Although steps are now being taken to develop these standards (Sect. 59.5.3), the situation is likely to persist for a number of years. In addition to the time it will take to develop the required standards, there will be a significant lag at the equipment manufacturers' end, associated with the rolling out of new products that align with these new standards.

Other challenges to the implementation of robotics technology in mining include:

- Reliability, availability, and fail-safe operation with graceful failure
- Ability to sustain productivity at current or better levels
- Mining in extreme environments and difficulties in developing the required supporting infrastructure
- Current design methodologies for mines and mining systems are not geared to support robotic systems
- Deploying systems in the field and the fact that every mine is different
- Provision of technical support, shortfall in skilled labor, lack of adequate training
- Poorly designed or challenging man-machine interfaces.

59.4.2 Socioeconomic Challenges

The resource industry has a conservative history, and the implementation of new technology and processes must overcome significant inertia. In general, the attitude of people, from those at the working face to senior managers and company executives, mirrors the attitude of the workforce in the manufacturing industry in the early days of industrial robotics; i.e., skepticism about technology and fear of losing one's job. The generational change is likely to alleviate the fear of technology, but robots will be regarded by many in the workforce as a *competitor* for years to come.

Some researchers in human factors also point to the over-reliance on the technology by operators as a possible outcome of spreading robotic systems in the industry. As a common trend across several domains, it was noted that automation and new technologies can sometimes result in operators engaging in more risky behaviours in automated systems [59.124].

Legal issues and insurance are two other factors that could create significant headwinds to the rapid proliferation of autonomous systems in mining or in other civilian activity for that matter. Actuarial analysis is very hard to do for a green field, such as commercial autonomous operations.

59.5 Challenges, Outlook, and Conclusion

This section briefly summarizes some of the primary challenges for robotics in mining, as well as examines some emerging themes within the field of mining robotics, beginning with those on the Earth and followed by a short discussion about planetary exploration and extra-terrestrial mining, all of which will rely heavily on robotic tools. The section ends with a short conclusion about the future outlook for mining robotics.

59.5.1 Technical Challenges

Despite the recent uptake of robotics technologies in mining, significant challenges remain. One expression that could be used to describe the current status of robotics in mining is *islands of automation*. This reflects the significant integration issues that exist in relation to fully autonomous, as well as mixed autonomous/manual/remote robotic equipment. One specific challenge, for example, is the lack of standards to which the various equipment manufacturers and technology developers should align. Although,

steps are now being taken to develop these standards (Sect. 59.5.3), it may take some time before equipment manufacturers roll out commercial products that adhere to these standards.

Some other key challenges for mining robotics include:

- Reliability, availability, and fail-safe operation with graceful and safe failure modes for very large equipment and (often) electric or hydraulically actuated equipment.
- Ability to sustain productivity at current or better levels when compared with current methods and systems.
- Mining in extreme and unstructured environments (e.g., far north, very deep underground, in harsh weather) and the difficulties in developing and supporting the necessary infrastructure in these environments.
- Current mining methods and design methodologies need to evolve so as to inherently incorporate robotic systems.

- Field robotics deployment challenges and the fact that every mine is different.
- Provision of technical support in remote areas, shortages of skilled labor, and the need to re-train existing personnel.
- Developing effective man–machine interfaces.
- Safely managing the colocation of robotic machines and human workers.

59.5.2 Socio-Economic Challenges

For the most part, the resource industry has a conservative history and the implementation of new technologies and processes must often overcome significant resistance to change. In many cases, the attitudes of people – from those at the working face to senior managers and company executives – mirror the attitudes of the workforce in the manufacturing industry in the early days of industrial robotics; i.e., skepticism about technology and fear of losing one's job. However, generational changes are likely to alleviate these challenges.

Some researchers in human factors engineering also point to the risk of over-reliance on technology by operators as a possible negative outcome of the proliferation of robotic systems. As a common trend across several domains, it was noted that automation and new technologies can sometimes result in operators engaging in more risky behaviours [59.124], which would not be looked favorably upon in mining.

59.5.3 Emerging Frontiers

There are several emerging frontiers for mining robotics, from the creation of standards to robots that improve safety in mining, and future-looking robots for mining asteroids and other extra-terrestrial bodies.

Emerging Standards for Mining Robotics and Automation

Due to the increasing prevalence of automation in mining, there is an immediate need to formulate standards for robotic equipment such that data may be exchanged freely among systems developed by different manufacturers. Currently, a tension exists between manufacturers, for whom it may seem the commercial imperative to design *closed* vertically integrated systems, and the mine operators, who would like any system they purchase to interoperate with all existing items of equipment.

There currently exists a data interchange standard known as the International Rock Excavation Data Exchange Standard (IREDES) [59.125]. This standard

uses the extensible markup language (XML) to define a three-level architecture:

1. Administration level that defines reusable data objects such as coordinate systems
2. Application profile level that covers general information for one application purpose
3. Equipment profile level that has detailed equipment specific information.

The IREDES standard currently covers drill rigs and LHD machines, with many prospective application profiles under active development.

There is also an ISO (International Organization for Standardization) standard called *Earth-moving machinery – Autonomous machine safety* (ISO 17757) [59.126] currently under active development. However, at the time of writing, there is no public information regarding this standard apart from its December 2012 approval. The standard will likely cover the risks inherent in large equipment automation, and common ways that those risks can be mitigated through design and/or procedure.

It is still early days for the standardization of autonomous mining machines, and current efforts are far from complete. However, it is a worthy goal, and one which will only increase in importance as more mining equipment is automated.

Mine Rescue Robots

Mining is inherently risky. Although infrequent today, many fatalities have occurred in mining and the necessity of a mine rescue strategy at every operation – particularly in underground mining – is clear. So why not use robots to assist with mine rescue?

Although not mainstream, mine rescue robots have been under development at a few research institutions, including at Sandia National Laboratories where researchers have focused on coal mines under funding from the United States National Institute for Occupational Safety and Health (NIOSH) [59.127]. In coal mining, the risk of explosions is high and poisonous gases may be present, particularly after a disaster. Their tracked Gemini Scout mine rescue robot is approximately 1.2 m long, equipped with an infrared camera (to see through smoke and dust) and gas sensors that allow rescuers to assess the situation before attempting a rescue.

More about mine rescue robots can be found in [59.128], including reference to the first known mine rescue robot prototype at the CSIRO, called Numbat [59.129].

Robotic Undersea Mining

There is a vast body of robotics research related to undersea applications and remotely operated underwater

vehicles (ROVs) (Chap. 51 of this book is dedicated to this topic). However, much of this work does not yet directly target undersea mining. Nevertheless, advances in robotics – specifically computer-based mapping, multivehicle coordination, as well as telerobotic drilling and excavation – are likely to make ocean floor mining a reality in the very near future.

Although the pursuit of marine mining dates back to the 1870s, large-scale operations have not yet been realized at least in part due to technological barriers [59.130]. Today, several venture mining companies, including most notably Vancouver-based Nautilus Minerals Inc. (TSE:NUS), are targeting polymetallic seafloor massive sulphide deposits. However, these resources are only accessible by using ROVs equipped with telerobotic seafloor production tools to disaggregate and collect the rock from the seafloor [59.131]. Thus, robotics is poised to play a significant role in undersea mining.

Planetary Exploration and Mining

Perhaps the next great frontier for mining is that of planetary exploration and resource extraction, whether for in-situ resource utilization (e.g., toward development of the Moon) or for return to the Earth (e.g., mining of asteroids for valuable materials).

Several enabling technologies that support autonomous off-world robotic excavation for large-scale habitat construction and resource extraction have already been developed. For example, researchers from the National Aeronautics and Space Administration (NASA) and CSIRO demonstrated remote excavation of a trench as an example of site preparation and regolith mining [59.132]. This remote excavation system consisted of a 1/7-th scale dragline excavator located at a CSIRO test facility in Australia, a control interface located at a NASA facility in the United States, and a communication network between the two. The tested use case scenario involved remote initiation of terrain mapping, and a click-to-dig user interface that allowed the specification of material transfer in terms of dig and dump points on the acquired terrain map. The terrain map was used to generate a collision-free

terrain-skimming path from dig to dump. The onboard path planner generated a bucket trajectory that included engaging the dig face (bank), filling the bucket and disengaging the bank. Tool force sensing was used as an input to the planner in order to constrain the dig speed and dig trajectory to remain within the operational limits of the machine and ensure adequate material flow into the bucket. The system successfully completed 50 consecutive cycles without any operator intervention. The average cycle time was approximately 63 s with the entire mission taking 52 min to complete.

There is also a thriving space exploration community, particularly within the mobile robotics community, and there is a complete chapter of this book dedicated to space robotics, Chap. 55. However, it is worth mentioning here that mining and planetary resource extraction have much in common and there is increasing cooperation between planetary geologists, mining equipment suppliers, and roboticists in problems related to Lunar and Mars exploration (e.g., see [59.4, 5, 133] and references therein for examples). Moreover, new commercial ventures, such as the widely publicized Planetary Resources, Inc., have been established with the aim of pursuing commercial extra-terrestrial resource discovery and utilization.

59.5.4 Conclusion

The desire to improve productivity, safety, and lower the costs of mining is a key motivator for the use of robotics in the mining industry. As highlighted in this chapter, several robotics-related advances have been made in recent history, for both surface and underground mining environments and, after a long courting period with robotics and automation, many mining companies are embracing robotics as a credible and practical tool. Moreover, with the emergence of *field robotics* as an increasingly popular subfield within the robotics research community, as well as the recent formation of networks, centers, and institutes that focus specifically on field robotics (some on mining), the domain of mining robotics appears poised to undergo accelerated growth on the Earth, undersea, and beyond.

Video-References

-  VIDEO 142 Autonomous tramming
available from <http://handbookofrobotics.org/view-chapter/59/videodetails/142>
-  VIDEO 145 Autonomous haulage system
available from <http://handbookofrobotics.org/view-chapter/59/videodetails/145>
-  VIDEO 718 Autonomous loading of fragmented rock
available from <http://handbookofrobotics.org/view-chapter/59/videodetails/718>

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Multimedia Contents



60. Disaster Robotics

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Rescue robots have been used in at least 28 disasters in six countries since the first deployment to the 9/11 World Trade Center collapse. All types of robots have been used (land, sea, and aerial) and for all phases of a disaster (prevention, response, and recovery). This chapter will cover the basic characteristics of disasters and their impact on robotic design, and describe the robots actually used in disasters to date, with a special focus on Fukushima Daiichi, which is providing a rich proving ground for robotics. The chapter covers promising robot designs (e.g., snakes, legged locomotion) and concepts (e.g., robot teams or swarms, sensor networks), as well as progress and open issues in autonomy. The methods of evaluation in benchmarks for rescue robotics are discussed and the chapter concludes with a discussion of the fundamental problems and open issues facing rescue robotics, and their evolution from an interesting idea to widespread adoption.

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Robots serve as extensions of emergency professionals. During the immediate response to a disaster, robots can provide real-time data about the event and perhaps even directly aid in inserting mitigation devices

and sensors, turning valves, and moving equipment. As the immediate life-saving and stabilization phase of the disaster ends, robots can help with the economic recovery. Robots for disaster are an emerging technology,

and have not yet been widely adopted by the international emergency response community. However, as of 2012, they have been used in 28 disasters in Cyprus, Haiti, Italy, Japan, New Zealand, and the United States primarily for mining disasters and structural collapses or infrastructure damage. Robots have been used for hazardous materials accidents, often referred to as chemical, biological, nuclear, radiological, or explosive (CBRNE) events, most recently the Fukushima Daiichi nuclear accident. Both structural and CBRNE events are generally handled by urban search and rescue teams unless an industry-specific team assumes command. As a result of the breadth of the term *urban search and rescue* contributes to a misperception that disaster robotics is limited to urban or constructed environments. For example, although technically an urban event, wilderness search and rescue is often conducted by a local urban search and rescue team. In general, disaster robotics connotes extraordinary situations requiring special operations; fire fighting is not considered as part of disaster robotics as it is a *routine emergency*.

Disaster robotics can contribute to broad area activities, local incidents, and routine emergencies,

though this chapter will focus on the use of robots for disaster events. Interest in robotics for surveying wildland fires and flooding is emerging, and the few documented uses of robots are reported in this chapter. Robots are also being increased use in local incidents which do not qualify as true disasters. For example, several fire rescue departments in Japan and the United Kingdom routinely use small underwater robots for water-based search and recovery of drowned victims and the interest in the use of aerial vehicles for wilderness search and rescue is growing.

Disaster robots have not been widely adopted, but their use is increasing as the technology matures. The general lack of adoption is to be expected since the technology is new and the concept of operations for these novel technologies take time to evolve. Rescue applications are often similar enough to military operations that the same platforms can be adapted; however, some tasks are significantly different than their military counterpart, some are unique to rescue, and the human–robot interaction for civilian response diverges from military patterns of use.

60.1 Overview

Disaster response is always a race against time, to move as fast as possible to reach all potential survivors and yet move slowly enough to avoid creating additional collapses, damage, risk to rescuers and victims, or contention over airspace. The primary motivation is to save lives; robots can assist in meeting this goal either by interacting directly with victims or structures or automating support activities.

60.1.1 Motivation

Disasters are defined as a discrete meteorological, geological, or manmade event, that exceeds local resources to respond and contain. Disasters are distinct from an ongoing condition such as global warming. In practice, a disaster means that an agency has to engage additional specially trained experts and equipment. For example, a chemical spill may be routine and handled with existing personnel trained in hazardous materials or it may be horrific, such as the 1984 Bhopal disaster that killed thousands of people.

Disaster activities are often referred to by phases, though there is no single accepted model in emergency management. After an event, public officials are responsible for the life-saving *response* and economic *recovery* activities focused on maximizing benefit to the

largest population. Nongovernmental agencies may join with other officials and citizens in humanitarian *relief* efforts which are generally focused on benefiting individuals. Emergency professionals are also tasked with *prevention* of disasters and *preparation* should there be sufficient warning.

Disaster response activities are typically executed by the urban search and rescue (USAR) task force within a fire rescue agency who work with law enforcement, transportation officials, and others. USAR is often used synonymously with any response activity. The term *urban* can be misleading as it sounds like it is restricted to building collapses. USAR includes hazardous material response, as these materials most certainly have something to do with built structures. USAR includes *wilderness search and rescue* which often involves searching tunnels and abandoned mines, avalanches, not just locating lost hikers. It also includes *water-based search and rescue* which deals with saving victims of floods or high currents (also known as *swift water rescue*) or in the aftermath of traffic accidents where victims are trapped in cars that have plunged into a river or bay. Water-based search and rescue does not necessarily have urban structures but there is a similarity of rescue techniques and re-use of equipment.

Historically, disaster robotics concentrated on the response phase of a disaster. The disaster robotics community began to form in 1995 as the outcome of the tragic loss of life in the Hanshin–Awajii earthquake in Kobe, Japan, and the bombing of the Murrah Federal Building in Oklahoma City, United States [60.1, 2]. In both cases, it was easy to imagine how small ground robots may have been able to enter rubble to find trapped victims. As a result, research efforts began in individual laboratories. Two mobile robot competitions (the AAAI (Association for the Advancement of Artificial Intelligence) mobile robot competition in the United States, and the RoboCup rescue league internationally) were started in the late 1990s to engage the scientific community in rescue research. The first use of robots for response was at the 2001 World Trade Center (WTC) disaster, where ground robots were used to penetrate the deeply packed rubble. Since then robots have been used for response to earthquakes, hurricanes, mine collapses, bridge collapses, explosions, and flooding.

The deployment of disaster robots during the response phase offers many potential benefits. The 2010 World Disasters report [60.3] suggests just how many lives have been, and will be, impacted by urban disasters. Over 1.1 million people were reported killed from 2000 to 2009, with the total amount of disaster-related damage estimated at 986.7 billion US dollars. Of the victims in urban disasters, only a small fraction may actually survive. Consider from [60.4, 5] that the majority of survivors (80%) of urban disasters are surface victims, that is, the people lying on the surface of the rubble or readily visible. However, only 20% of survivors of urban disasters come from the interior of the rubble, yet the interior is often where the majority of victims are located, providing motivation for robots that can explore deep within collapses. The mortality rate increases and peaks after 48 h, meaning that survivors who are not extricated in the first 48 h after the event are unlikely to survive beyond a few weeks in the hospital.

However, disaster robotics is no longer focused on response but has expanded to recovery. Recovery activities consist of extricating any remaining bodies of victims, re-establishing normal operations in the community, continuity of government, and resumption of the economy. The activities are typically carried out by various local, provincial, state, and federal agencies as well as insurers and banks. Each municipality may have different priorities in rebuilding schools, hospitals, ports, and industry and there is usually no centralized authority.

The benefits of disaster robotics for the recovery phase were seen in the ongoing aftermath of 2011 Tohoku earthquake and related Fukushima Daiichi nuclear accident. The tsunami generated by the earthquake

swept thousands of people into the sea. It also severely damaged many fishing ports and scattered debris and pollutants throughout fishing areas. Teams of robotists used underwater robots to search for victims and to help re-open ports and clear fishing beds. The decommissioning of the Fukushima Daiichi facility will make use of robots, possibly some of those used in the response.

Disaster robotics is also addressing prevention and preparedness. As with recovery operations, prevention and preparedness activities are similarly distributed among many groups. It should be noted that the fire rescue and law enforcement teams will be the first responders and whatever equipment they use locally will be likely to be used at a disaster. Therefore, the disaster robotics community has begun pushing for the adoption of robots into daily use by fire rescue and bomb squads so that the responders will be familiar and comfortable with the technology [60.6]. A lesson from Fukushima was that robots built by the nuclear industry in the aftermath of Chernobyl and Three Mile Island had not been used in decades, with no one expert in their use.

60.1.2 Disaster Robot Tasks

While the overall motivation for rescue robotics is to save lives, the motivation for specific robot designs and capabilities depend on their potential tasks. The types of tasks that have been proposed for rescue robots are described below. Some of the above tasks are similar to tasks for military robots, especially search and reconnaissance and mapping, but many are unique or have a different flavor. For example, structural inspection, rubble removal, and adaptively shoring rubble are rescue specific. Tasks such as casualty extraction appear to be similar but are significantly different. Consider that a wounded soldier is unlikely to have a spinal cord injury and is likely to be in a space large enough for a human to work in, so a robot entering the area and dragging the soldier to safety is appropriate. However, a crushed victim of a building collapse is physically trapped or pinned in a small space, requiring rubble removal, and the victim's spinal cord must be immobilized before extraction; clearly victim extraction in the search-and-rescue domain is more challenging.

Search is a concentrated activity in the interior of a structure, in caves or tunnels, or wilderness and aims to find a victim or potential hazards. The motivation for the search task is speed and completeness without increasing risk to victims or rescuers.

Reconnaissance and mapping is broader than search. It provides responders with general situation awareness and creates a reference of the destroyed en-

vironment. The goal is speedy coverage of a large area of interest at the appropriate resolution.

Rubble removal can be expedited by robotic machinery or exoskeletons. The motivation is to move heavier rubble faster than could be done manually, but with a smaller footprint than that of a traditional construction crane.

Structural inspection may be either conducted on the interior (e.g., to help rescuers understand the nature of the rubble in order prevent secondary collapses that may further injure survivors) or on the exterior (e.g., to determine whether a structure is safe to enter). Robots provide a means of getting structural sensor payloads closer and in far more favorable viewing angles.

In situ medical assessment and intervention are needed to permit doctors and paramedics to interact verbally with victims, visually inspect the victim or apply diagnostic sensors, or to provide life support by transporting fluids and medication through narrow tubing. The objective is to provide telepresence for medical personnel during the 4–10 h that it usually takes to extricate a victim [60.4, 5]. The lack of medical intervention was a major problem at the Oklahoma City bombing [60.7]. Preliminary work has been conducted for victim management, most notably in telemedicine (also called *medical reachback*) [60.8], general assessment and triage [60.9], and comforting trapped victims as per the Survivor Buddy project [60.10].

Medically sensitive extrication and evacuation of casualties may be needed to help provide medical assistance while victims are still in the disaster area, also known as the hot zone. In the case of a chemical, biological, or radiological event, the number of victims is expected to exceed the number that can be carried out by human rescuers in their highly restrictive protective gear; this makes robot carriers attractive. Since medical doctors may not be permitted inside the hot zone, which can extend for kilometers, robot carriers that support telemedicine may be of huge benefit. Removing survivors, particularly from a hazardous material event where there may be many people immobilized or disoriented is another area that is getting increasing attention. The US Army Telemedicine and Advanced Technology Research Center has been leading initiatives in robots such as the Vecna BEAR for autonomous casualty extraction [60.11]. Other efforts such as those by Yim and LaCharoen [60.12] have focused on civilian casualty extraction which requires stabilization of the spine.

Acting as a mobile beacon or repeater to extend wireless communication ranges, enable localization of personnel based on radio signal transmissions by providing more receivers, and to serve as landmarks to allow rescuers to localize themselves. Active or passive

transponders such as wireless sensor nodes and **RFIDs** (radio-frequency identification) can be deployed in the field. They can also be used to support the localization of personnel, but even more to leave mission-related data such as the location of nearby victims and hazards in the field [60.13].

Serving as a surrogate for a team member, such as a safety officer or a logistics person. In this task, the robot works side-by-side with rescuers, for example, a group breaching rubble deep within the interior of a disaster may have difficulty using a radio to request additional resources because of noise. However, a team member outside of the rubble can see and hear through the robot the state of progress and anticipate needs. The objective is to use robots to speed up and reduce the demands of tasks, even if they are done by humans.

Adaptively shoring unstable rubble to expedite the extrication process. Rubble removal is often hindered by the need to adopt a conservative pace in order to prevent a secondary collapse that might further injure a trapped survivor.

Providing logistics support by automating the transportation of equipment and supplies from storage areas to teams or distribution points within the hot zone.

60.1.3 Types of Disaster Robots

Rescue robots are needed to help quickly locate, assess, stabilize, and extricate victims who cannot be easily reached. They typically do this by extending the rescuers' ability to see and act. On the ground, small unmanned ground vehicles (**UGVs**) can enable rescuers to find and interact with trapped victims in voids that are too small or too dangerous for human or canine entry. Large **UGVs** can accomplish tasks such as removing large rubble faster than humans. In the air, unmanned aerial vehicles (**UAVs**) robots extend the senses of the responders by providing a bird's eye view of the situation. In the water, unmanned marine vehicles (**UMVs**), either underwater vehicles (**UUVs**) or surface vehicles (**USVs**) robots can similarly extend and enhance the rescuers' senses.

Rescue robots can be broadly categorized into types based on *modality* and *size* [60.14], though other taxonomies that mix modality, size, and task have been proposed [60.15]. There are three modalities of robots: *ground*, *aerial*, and *marine*. The modality impacts on the basic design and capabilities of the robot. Within each modality, rescue robots can be further described as one of three sizes: *man-packable*, *man-portable*, and *maxi*. The size of the robot impacts both on the tasks for which it is suited and how soon after a disaster it might be used. In order to be man-packable, the entire robot system, including the control unit, batteries,

and tools, must fit into one or two backpacks. Man-packable robots are more likely to be used immediately after a disaster since they can be carried by responders over debris and up and down ladders into the core of the disaster, while larger equipment must wait for paths to be carved out. The next larger size is man-portable; these are robots that can be carried a short distance by two people or on a small all-terrain vehicle. Man-portable robots function in human-sized spaces such as mine tunnels. They can be used as accessibility within the hot zone improves or outside the hot zone for logistics support. Maxi-sized robots require trailers or other special transportation logistics. This inhibits their insertion into the hot zone.

Aerial rescue robots represent the most advanced robotics technology in use, and new concepts continue to emerge. Aerial vehicles can be further subdivided into *fixed wing* (plane-like), *rotary wing* (helicopters),

lighter-than-air (blimp), and *tethered* (kite) platforms. Fixed-wing UAVs typically travel long distances and can circle points of interest, while rotary-wing platforms can hover and require a small area to launch and land. Lighter-than-air vehicles may be tethered, similar to a kite. Underwater vehicles may also be subdivided into tethered and untethered platforms.

Large unmanned helicopters, such as the Yamaha R-Max, continue to be adapted for commercial rescue-and-recovery missions, including carrying heavy payloads capable of estimating the amount of rubble and debris generated by a disaster. Small fixed-wing platforms for tactical military use may have great benefit to the response community. However, UAVs are drawing the attention of agencies that control airspace and may become heavily regulated in the future. For example, the small UAV used at Haiti in 2010 flew in violation of airspace restrictions.

60.2 Disaster Characteristics and Impact on Robots

The type of disaster as well as the general pattern of activity influence the choice of robot platforms and payloads.

60.2.1 Natural Disasters

Natural disasters, such as earthquakes, tsunamis, hurricanes and typhoons, volcanoes, avalanches, landslides, and floods, present many challenges for rescue robots. Natural disasters are usually geographically distributed, perhaps affecting a 200 km or more radius around the epicenter of the event. The sheer size of the affected area presents many challenges to the emergency response. The primary impact of natural disasters is on residences, light commercial buildings, sea walls and canals, and transportation and communications infrastructure. This implies that rescuers have thousands of structures to check quickly for survivors, but those structures will be fairly small and amenable to manual and canine search. Besides the sheer volume of structures to check, communication disruptions prevent rescuers from getting timely information as to the state of transportation access and the general needs of an area. However, designing robots to meet these challenges is important because natural disasters provide the most hope of a large number of survivors. Uninjured survivors may simply be stranded and can survive for up to 72 h. Natural disasters have generally favored a bird's eye view from a UAV invaluable in establishing situation awareness or UGVs in determining *hidden* conditions of critical transportation, power, and communication infrastructure.

60.2.2 Manmade Disasters

In comparison to natural disasters, manmade disasters (such as a terrorist bombing or an industrial accident) occur in a small area, though may have significant wide-area impacts (e.g., radiation, chemical release). The challenge is often not how to see the entire external extent of the damage, but rather to see what is not visible: the interior of the rubble, the location and condition of survivors, the state of potentially dangerous utilities (e.g., electricity, gas lines) [60.14, 16, 17], and hazardous conditions such as radiation [60.18]. The communications and power infrastructure usually exist within a 10 km range and cell phones generally work outside of the directly affected area. Voids in the rubble may be irregular in shape and vertical in orientation. Wireless communications in the interior of the rubble are unpredictable, and generally nonexistent due to the large amount of steel within commercial structures, but the combination of irregular voids and sharp rubble do not favor the use of fiber optic cables. Visibility is difficult as there is no lighting and everything may be covered with layers of gray dust, further hampering recognition of victims, potential hazards, or accurate mapping. The interiors may be wet or contain standing water due to water lines, sewers, and sprinkler systems. Survivors are more likely to be in dire need of medical attention. Small ground robots that can enter deep into the interior of the rubble have been used most frequently for structural collapses, mid-sized robots for CBRNE events, and large, intrinsically safe robots for mine collapses.

60.2.3 General Pattern of Activity During the Response Phase

In order to understand how to apply robotics to disaster response (as opposed to recovery or prevention and preparedness), it is helpful to understand the general pattern of activity, which can be summarized as [60.19, 20]:

1. Responders become aware of the existence of victims. This awareness may be generated by information from family, neighbors, and colleagues, an understanding of demographic patterns (e.g., at night, apartment buildings will be heavily occupied, while during a work day, office buildings will be occupied), or by a systematic search.
2. The response command staff attempt to understand the disaster site. They investigate the site for conditions such as hazardous materials, the risk posed to the rescuers themselves, any pending threats to trapped victims, and resource restrictions such as barriers to transporting resources to the site,
3. The command staff plans the operations.
4. Search and reconnaissance teams are sent to map the situation and assess environmental conditions. Accurate estimates of the need for emergency medical intervention are highly desirable in order to optimize allocation of medication personnel in the field and to prepare ambulances and hospitals. (In the case of the Kobe earthquake, this stage took the longest time [60.19].)
5. Excavation of rubble to extract victims begins. Note that removal of rubble in search and rescue differs from construction removal of rubble, because the safety of the victims is the top priority.
6. Responders gain access to victims and apply emergency medicine in situ.
7. Victims are transferred to hospitals.
8. Field teams report activities periodically, usually at the end of the shift, and the command staff modifies or replans accordingly.

60.3 Robots Actually Used at Disasters

Small land, aerial, or marine vehicles have been used at 28 disasters and numerous local events, starting with the first use of **UGVs** at the 2001 World Trade Center collapse, see Table 60.1. The majority, 16, have taken place in the United States, followed by Japan (3), Italy (3), New Zealand (2), Haiti (1), Thailand (1), Cyprus (1), and Canada (1). The May 2013 rescue by a **UAV** guiding searchers to an injured motorist who had wandered from his car in Canada is the first reported *live save* of a person by a robot. However, as noted earlier, directly saving lives is not the only motivation for a robot. Robots have received in general high marks for completing their missions. Table 60.1 shows 37 reported deployments of robots for a disaster or well-known local incident. The deployments are grouped by major general disaster type of event: meteorological (e.g., hurricane, earthquake), geological event (e.g., earthquake, tsunami), man-made (e.g., terrorism, industrial accident), or mining (either due to a geological or a man-made event). Mine and manmade disasters are most frequent, followed by geological and meteorological events. In 7 of the 37 events, robots were present but were not used or could not reach the area of interest and thus considered not successful. **UGVs** have been used most frequently, followed by **UAVs**, and **UMVs**. While the USA initially led in reported adoptions, Europe and Asia are beginning to deploy

robots. This section discusses the deployments by the four disaster types, while the following section highlights the 2011 Fukushima Daiichi nuclear accident as it highlights the types of robots, missions, and challenges posed during both the response and recovery phases of a disaster.

60.3.1 Meteorological Events

Robots were used at six meteorological events and were successful at five:

- 2005 Hurricane Katrina (USA), where an Inuktun ASR Xtreme **UGV** [60.21], an Aerovironment Raven fixed wing **UAV** and a Like90 helicopter **UAV**, and a Silver Fox fixed wing **UAV** were used during the initial response phase for search, reconnaissance and mapping, and structural inspection [60.22]. Later an iSENSYS IP3 was used for structural inspection during the recovery phase [60.23]. The **UGV** searched an apartment building unsafe for human entry and the **UAVs** surveyed areas inaccessible by car. The two **UAVs** used during the response are shown in Fig. 60.1 – a battery-powered fixed-wing and a battery-powered rotary-wing (a Like90 T-Rex miniature helicopter modified for stability in high winds) **UAVs**.

Table 60.1 The modalities and numbers of robots deployed to actual disasters and whether they were successful or not

Disaster or notable incident		Disaster type of event				Robots used			Success
		Meteoro-logical	Geo-logical	Manmade	Mining	Ground	Aerial	Marine	
2001	World Trade Center (USA)			✓		4			✓
2001	Jim Walters No. 5 mine (USA)				✓	1			✗
2002	Barrick Gold Dee mine (USA)				✓	1			✓
2004	Brown's Fork mine (USA)				✓	1			✓
2004	Niigati Chuetsu earthquake (Japan)		✓				1		✓
2004	Hurricane Charley (USA)	✓				1			✗
2004	Excel #3 Mine (USA)				✓	1			✓
2005	DR No. 1 mine (USA)				✓	1			✓
2005	McClane Canyon mine (USA)				✓	1			✓
2005	La Conchita mudslides (USA)		✓			1			✗
2005	Hurricane Katrina (USA)	✗				1	3		✓
2005	Hurricane Wilma (USA)	✓					1	1	✓
2006	Sago mine (USA)				✓	1			✗
2006	California wildfires (USA)	✓					1		✓
2007	Midas gold mine (USA)				✓	2			✓
2007	Crandall Canyon mine (USA)				✓	1			✓
2007	I-35 Minnesota bridge collapse (USA)			✓				2	✓
2007	Berkman Plaza II collapse (USA)			✓		2	1		✓
2008	Hurricane Ike (USA)	✓						1	✓
2009	Cologne State Archives collapse (Germany)			✓		2			✗
2009	L'aquila earthquake (Italy)		✓				1		✓
2010	Haiti earthquake (Haiti)		✓				1	1	✓
2010	Wangjialing coal mine (China)				✓	1			✗
2010	Upper Big Branch mine (USA)				✓	1			✗
2010	Deepwater Horizon (USA)			✓				16	✓
2010	Prospect Towers (USA)			✓		2			✓
2010	Missing balloonists (Italy)			✓				1	✓
2010	Pike River mine (NZ)				✓	2			✓
2011	Christchurch earthquake (NZ)		✓			1	1		✓
2011	Tohoku earthquake (Japan)		✓			3	1		✓
2011	Tohoku tsunami (Japan)		✓					9	✓
2011	Fukushima nuclear emergency (Japan)			✓		7	2		✓
2011	Naval base explosion (Cyprus)			✓			2		✓
2011	Thailand floods (Thailand)	✓					2		✓
2012	Costa Concordia (Italy)			✓				2	✓
2012	Finale Emilia earthquake (Italy)		✓				2		✓
2012	Missing person RCMP (Canada)			✓			1		✓
Total	37	6	8	11	12	23	13	8	37

- 2005 Hurricane Wilma, Ft. Myers, Florida (USA), where an AEOS unmanned marine surface vehicle (Fig. 60.2) and an iSENSYS T-Rex unmanned aerial vehicle were used independently and cooperatively, to assist with the recovery phase for structural inspection of buildings, docks, and piers [60.24]. The robots provided useful infor-

mation but the USV experienced significant wireless communications and GPS (global positioning system) signals near and underneath large structures.

- 2006–2010 California wildfires (USA), where the National Aeronautics and Space Administration Ikhana Global Hawk was used to provide recon-

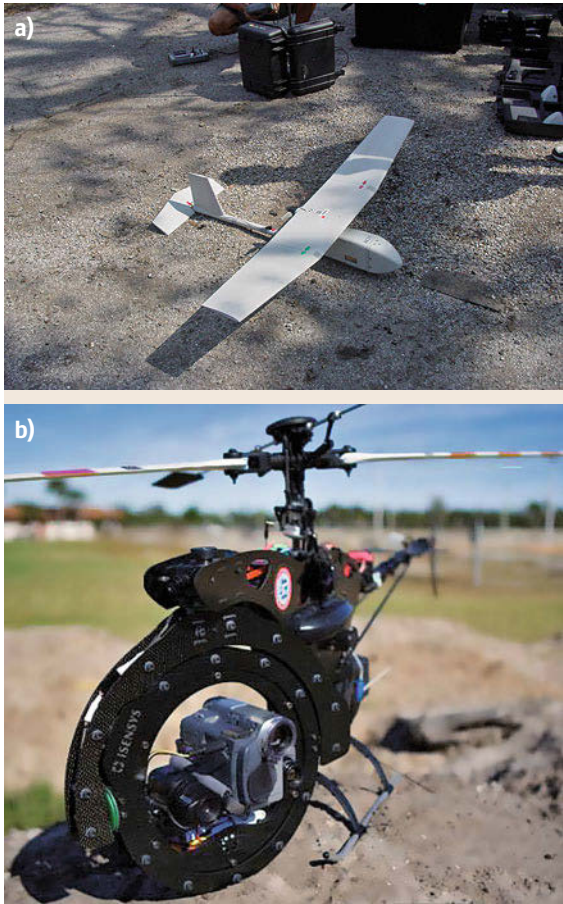


Fig. 60.1a,b Man-packable UAVs used to search portions of Mississippi during the hurricane Katrina response: (a) an Aerovironment Raven fixed-wing UAV and (b) an iSENSYS IP3 rotary-wing UAV (courtesy of CRASAR)



Fig. 60.2 Unmanned surface vehicle exploring the bridge to Marco Island, Florida (courtesy of CRASAR)

naissance and mapping of 57 fires [60.25]. Ikhana was primarily used to gather data to develop new payloads but did contribute in 2010 to tactical response.

- 2008 Hurricane Ike, Rollover Pass Bridge, Texas (USA), where an AEOS unmanned marine surface vehicle, a VideoRay remotely operated vehicle (ROV), and a YSI Oceanmapper autonomous underwater vehicle (AUV) were used for structural inspection of the Rollover Pass bridge [60.26]. The USV was able to confirm the lack of scour around the pilings while the VideoRay could not be controlled in the high currents and the YSI AUV could not accurately preplan its path without colliding with the structure.
- 2011 Thailand floods (Thailand), where two unmanned UAVs provided reconnaissance and mapping of flood plains, allowing officials to concentrate evacuation or shoring efforts during the prevention and preparedness phases [60.27]. The UAVs are credited with mitigating damage to Bangkok and loss of life.

UGVs were present at 2004 Hurricane Charley (USA) but not used for the house-to-house inspection tasks that made up the bulk of ground operations [60.28].

60.3.2 Geological Events

Robots have been used at eight geological events (6 earthquakes, 1 landslide, 1 tsunami). They were successful at seven events:

- 2004 Niigata–Chuetsu Earthquake, where a variant of the Soryu III snake robot was used for search in collapsed houses. The snake robot was able to move into constricted passageways. Figure 60.3 shows the robot on site.



Fig. 60.3 IRS Soryu robot searching a house destroyed by the Niigata–Chuetsu earthquake (courtesy IRS)



Fig.60.4a–c Investigation of damaged building by Quince

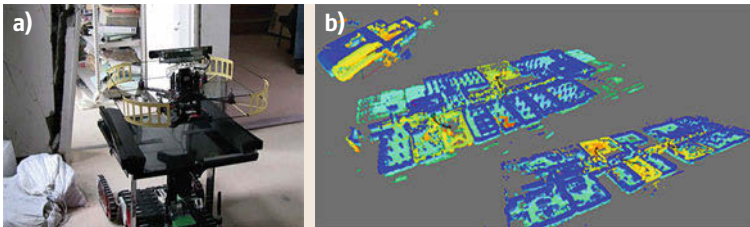


Fig. 60.5 (a) Docking system of Quince and Pelican, and (b) 3-D (three-dimensional) map measurement by collaboration

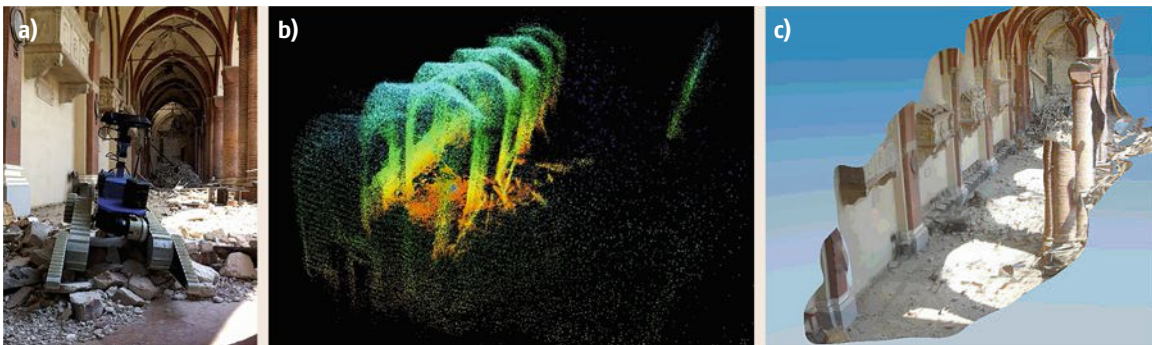


Fig.60.6a–c Finale Emilia earthquake: (a) the UGV platform deployed in the destroyed cathedral. (b) Reconstruction of the cathedral from laser measurements, (c) and image data

- 2009 L'aquila earthquake, L'aquila (Italy), where a customized AscTec quadrotor UAV was used for structural inspection. The UAV was able to fly successfully close to buildings and windows.
- 2010 Haiti earthquake (Haiti), where a SeaBotix LBV ROV was used for underwater reconnaissance and mapping of debris in shipping lanes and an Elbit Skylark UAV was used for reconnaissance and mapping of orphanages. Both the robots provide valuable information.
- 2011 Christchurch earthquake, Christchurch (New Zealand), where an iRobot Packbot UGV and a Parrot AR.drone UAV were used for structural inspection of the Christchurch catholic cathedral [60.29]. The Packbot was successful but the UAV's camera did not face upward and the ceiling could not be examined.
- 2011 Tohoku earthquake, Sendai (Japan), where a KOHGA3 and Quince UGVs (Fig. 60.4) and a Kenaf and Quince UGVs were used cooperatively with a Pelican UAV [60.30] (Fig. 60.5) for structural inspection of damaged buildings. The robots were able to provide information to structural engineers.
- 2011 Tohoku tsunami (Japan), where nine UGVs were used for reconnaissance and mapping, and victim recovery during the recovery phase. Five different teams deployed UGV: A SeaBotix SARbot, SeaBotix LBV-300, SeaMor, and Access AC-ROV were deployed by a joint IRS-CRASAR team in April 2011 and later again in October adding

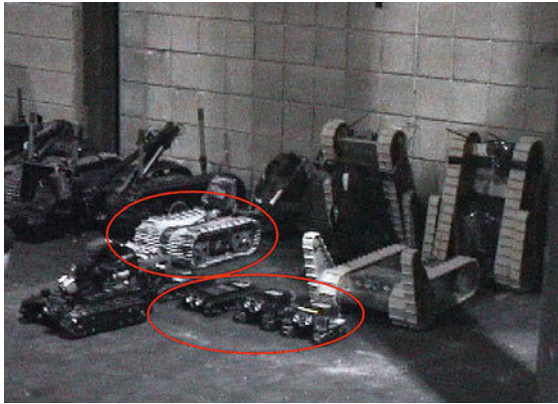


Fig. 60.7 Robots available at World Trade Center disaster. Ovals indicate the three types of robots used in the first two weeks (courtesy CRASAR)

a YSI Oceanmapper [60.31]; the IRS-CRASAR team was credited with reopening the port of Minamisanriku. Ura from Tokyo University fielded an unnamed ROV which recovered two dead bodies from an undisclosed location [60.32]. Prof. Shigeo Hirose at Tokyo Institute of Technology also created an experimental ROV and deployed with the Japanese Ground Self-Defense Forces [60.32]. IDEA Consultants (Japan) deployed their Mitsui ROV. Shibuya Diving Industry bought and used a VideoRay Pro 4, though the extent of the use is not known [60.33]. All UMVs were ROVs with the exception of the YSI Oceanmapper.

- 2012 Finale Emilia earthquake (Italy), where two custom unmanned aerial vehicles and two UGVs were used at Mirandola, Italy, for structural inspection of the exteriors and interiors of two churches that had not been entered due to safety reasons [60.34] (Fig. 60.6). The robots were able to provide information to the Italian National Fire Corps and state archaeologists.

An Inuktun VGTV Xtreme UGV was unsuccessfully deployed at the La Conchita mudslide to search for possible survivors in houses collaterally damaged by the mudslide [60.35]. The robot failed on its two runs within two minutes and four minutes, respectively, due to severe mud and thick shag carpeting.

60.3.3 Manmade Events

Robots were at nine manmade events. They were successful at eight events:

- 2001 World Trade Center collapse (USA) [60.36], where Inuktun Micro-Tracks, Inuktun Micro-VGTV, Foster-Miller mini-Talon, and Foster-Miller

Talon were used for search and reconnaissance and mapping in the interiors of the collapsed buildings (Fig. 60.7). The robots were able to penetrate farther than nonrobotic tools in spaces too small for human or canine entry.

- 2007 I-35 Bridge collapse, Minneapolis, Minnesota (USA) [60.37, 38], where two unspecified unmanned marine vehicles were used for search and reconnaissance and mapping underwater. The ROVs appeared to provide views without risking human divers in the fast moving currents.
- 2007 Berkman Plaza II parking garage collapse, Jacksonville, Florida (USA) [60.39, 40], where an Inuktun Micro-VGTV was used during the rescue phase for search and during the recovery phase an Active Scope Camera and an Inuktun ASR Xtreme were used for structural inspection along with an iSENSYS IP3 UAV for reconnaissance and mapping and structural inspection. The Micro-VGTV ruled out the presence of a survivor in areas too dangerous for a human to enter. The ASC and Xtreme provided structural forensic information that resolved legal liability and insurance coverage costs. The UAV provided imagery that led structural experts to hypothesize the cause of the collapse.
- 2010 Prospect Towers parking garage collapse, Hackensack, New Jersey (USA) [60.22], where an Inuktun VersaTrax 100 and an Inuktun VGTV-Xtreme were deployed for search. The robots were used to see vehicle information, license plates, makes and models in areas not safe for responders.
- 2011 Fukushima Daiichi nuclear accident (Japan) [60.18, 41], where seven UGVs and two UAVs were used for search, reconnaissance and mapping, and structural inspection. The robots provided damage assessment and radiological surveys without exposing workers to radiation. A UGV and a UAV were lost during the first year, but only after they provided important information.
- 2011 Evangelos Florakis naval base explosion (Cyprus) [60.17], where an AscTec Falcon and AscTec Hummingbird were used to inspect the damage to the adjacent Vasilikos power plant without requiring engineers to risk exposure to live unexploded ordinance. The UAVs were used for structural inspection. The operations were successful and led to a rapid repair of the power plant.
- 2012 Costa Concordia (Italy) [60.42, 43], where an Ageotec Perseo ROV and a VideoRay ROV, possible other unreported ROVs, were used for reconnaissance and mapping, structural inspections, and for victim recovery operations from the sunken cruise liner. The ROVs were considered essential in understanding the situation under the water.

- 2013 Missing person Royal Canadian Mounted Police (Canada) [60.44], where a Draganflyer X4-ES UAV with a thermal camera was used by the Royal Canadian Mounted Police to find an unconscious driver who had wandered from a car wreck. This is considered the first reported *live save* by a robot.

Robots were requested and present, but not used at the 2009 State Archives Building Collapse in Cologne, Germany, due in part to operator safety [60.45].

60.3.4 Mine Disasters

Robots were at 12 mining disasters. They were successful at seven events:

- 2002 Barrick Gold Dee mine, Elko, Nevada; 2004 Excel #3 mine, Pikesville, Kentucky; 2005 DR#1 mine, McClure, Virginia; 2005 McClane Canyon mine, Grand Junction, Colorado (USA), where



Fig. 60.8 The mine-permissible variant of the Wolverine robot used at the 2006 Sago Mine Disaster (courtesy of the US Mine Health and Safety Administration)



Fig. 60.9 The Inuktun VGTV-Xtreme robot being lowered into the Midas gold mine (courtesy of CRASAR)

a mine-permissible Remotec Wolverine (Fig. 60.8) was deployed the US Mine Safety and Health Administration (MSHA) used by to reopen mines that had been closed [60.46]. At the Barrick Gold Dee mine, the V-2 was deployed from the surface down a 16° slope and was able to navigate and to take continuous gas samples. At the Alliance Resources' Partners Excel #3 (coal) mine the robot was able to penetrate 230m into the mine and successfully completed the objective of providing an assessment of the situation. At the DR#1 Dixon-Russell (coal) mine the robot was able to penetrate 210 to 250 m into the mine with a slope of 18° and the robot arm was used to move and realign ceiling supports in order to progress into the mine. At the McClane Canyon (coal) mine trials were conducted to establish manipulation capabilities. In this case, the robot was tasked to close five doors and pull out timbers holding up a mine fan. The robot was generally unsuccessful with manipulation tasks.

- 2007 Midas gold mine, Midas, Nevada (USA), where an Allen-Vanguard from Fallon Naval Air Station and a Inuktun VGTV-Xtreme variant from the Center for Robot-Assisted Search and Rescue (CRASAR) were lowered into the mine and used for victim recovery [60.47]. Mine-permissible robots were not needed as the gold mine was not emitting methane. The Allen-Vanguard that was lowered into the void and found the machinery but not the victim. The Xtreme was able to penetrate 35 m vertically into the void (Fig. 60.9). The robot scanned the area where the body was recovered but did not have sufficient lighting to actually see the body.
- 2007 Crandall Canyon mine, Huntington, Utah (USA), where a custom Inuktun mine Cavern Crawler robot was deployed by US mine Safety and



Fig. 60.10 The Inuktun mine crawler robot being lowered into a borehole at the Crandall Canyon mine (courtesy of CRASAR)

Health Administration to search for missing miners (Fig. 60.10) [60.47]. The robot had to travel over 430 m through a 22 cm diameter borehole. Four attempts were made to enter the mine through two different boreholes, but only one was successful. In the fourth run, the robot was able to travel through the borehole then search about 2 m on the mine floor which was largely impassable due to the debris and drilling tailings. The robot provided no sign of the miners.

- 2010 Pike River coal mine, Greymouth (New Zealand), where two unknown New Zealand Defence Force bomb squad robots and Western Australia Water company pipeline inspection robot were used for search and recovery operations. The first New Zealand Defence Force (NZDF) robot ailed after reaching 550 m into the mine due to falling water, but was successfully restarted and moved out of the way of the second robot before running out of battery power. The first and second robots were presumed destroyed in a second explosion that ended any expectations of survivors. The

pipeline inspection robot was later used for recovery operations.

Robots were unsuccessful at two events. At the 2004 Browns Fork mine, Hazard, Kentucky, disaster, the Wolverine robot was too tall to go into the area of interest to conduct a search. At the 2006 Sago mine Disaster, Sago, West Virginia (USA), the robot was only able to penetrate about 700 m into the mine before being damaged when it accidentally was driven off the path and flipped over [60.46].

Robots were on-site but not used at three events: the 2001 Jim Walters #5 mine fire (USA) as the robot was not mine-permissible, the 2010 Wangjialing coal mine (China) presumably because the unidentified robot could not transit high water, and the 2010 Upper Big Branch mine (USA) where the restricted confines posed too great a risk of failure. Robots were requested for the 2010 San Jose Copper-Gold mine (Chile) and the 2011 San Juan De Sabinas coal mine (Mexico) disasters but robots were not small enough and thus were not sent.

60.4 Robots at the Fukushima-Daiichi Nuclear Power Plant Accident

The Fukushima-Daiichi nuclear power plant accident merits special attention because robots have been used for both the response and recovery phases. The use of robots have been sustained over months and years, and a wide variety of robots have been used.

Control over the reactors at the Fukushima-Daiichi nuclear power plant was lost on March 11, 2011, after a 14 m high tsunami from the Eastern Japan Earthquake submerged the facility. Units 1–3 melted down, hydrogen exploded at the high floors of nuclear reactor buildings of Units 1, 3, and 4, and huge amounts of radioactive materials were released to the wide area centered by Fukushima Prefecture. Robots were used during the prolonged response phase for assessment of the emergency situation and mitigation of the event by recovering the cooling systems to enable a cool shutdown. After four months, the immediate response turned to preparation for decommission as the reactors were stabilized. The recovery phase requires operations in the contaminated area; therefore, many robotic systems have been, and are continuing to be, used for minimizing workers' exposure to radiation by substituting for human operations. In the first year, ground and aerial robots were used for exterior operations outside the buildings and ground robots for interior operations inside the reactor buildings.

60.4.1 Exterior Operations

Robots were used outside the buildings and on the grounds by different teams for four applications: debris removal, structural inspection, radiological surveys, and mitigation efforts.

Debris Removal by Unmanned Construction Machines

There was a large amount of contaminated debris outside the building producing a high dose rate of a few hundred mSv/h, preventing workers accessing the buildings. Debris removal operations were conducted starting April 1, 2011 for nine months using an adaptation of unmanned construction robot machines had been developed for the restoration work after the *Unzen Fugen-dake Volcano* eruption in 1991 (Fig. 60.11). Debris was gathered by two backhoes and a bulldozer, with wireless teleoperation, then loaded to containers on two remote-controlled crawler dump trucks, and carried to storage yards of contaminated materials. The crawler dump trucks were teleoperated from a remote operator car, with command and control signals and data from camera and sensors transmitted via a remote-controlled radio relay car. Seven camera cars were connected to the system by wire, and external image views supported the task execution. As



Fig. 60.11a,b Unmanned construction machines used at Fukushima-Daiichi (courtesy of Unmanned Construction Machines Association)

a result, debris of 20 000 m³ was removed from the area 56 000 m² wide, and the radiation level reduced significantly to safely accessible level for the workers.

Structural Assessment and Radiological Surveys from T-Hawk UAV

A team led by Westinghouse used Honeywell T-Hawks from April 10, 2011, to the end of July, 2011 (Fig. 60.12). The team flew approximately 40 missions with two objectives originally. One was to investigate the state of the reactor and turbine buildings and to acquire video of the general area in order to support initial assessments of the incident and to help plan for debris removal. The second was to take radiological samples to produce a survey map. The objectives later expanded to off-site debris field survey, survey of the coastal breakwater structure, a gamma radiation survey at specific locations of interest to TEPCO, and airborne-particulate sampling (flying into plumes) at select locations.

Radiation Source Measurement by Gamma Cameras

The Japan Atomic Energy Agency (JAEA) developed a robot control car *TEAM NIPPON* with a gamma camera, a 3-D camera, a thermo camera, and a QinetiQ Talon robot that were provided by Idaho National Laboratory, a US federal laboratory that conducts research in nuclear reactors, in collaboration with Tohoku University. It was used from May 5, 2011 for measuring radiation of the outdoor debris, and provided visualized data as shown in Fig. 60.13 [60.18, 41].

Remote Control of Concrete Pumping Cars

Concrete pumping cars had been used for pouring water from outside in order to cool used-fuel pools on the

top floor of the exploded nuclear reactor buildings. In order to reduce the radiation exposure of workers who control their long arms, the cars were fitted for remote teleoperation by using remote controllers, cameras, and wireless equipment on May 2011.

60.4.2 Interior Operations in Nuclear Reactor Buildings

UGVs continue to be used for operations in the interior of the reactor buildings. UGVs were used to survey the interiors (iRobot Packbot, IRS Quince), monitor for gamma radiation (JAEA J-3), remove debris (QinetiQ Bobcat and Talon, Brokk), and experiment with decontamination (iRobot Warrior).

Survey of Nuclear Reactor Buildings by PackBots

On April 17, 2011, TEPCO workers and six engineers from iRobot used two donated PackBots to open the double hatch doors of Units 3 and 1, providing the first entry into those buildings (Fig. 60.14). The TEPCO workers carried the robots to the front of the hatch, and pointed an antenna to the robots from the glass window of the hatch. Based on the readings of radiation dose rate, temperature, humidity, and gas concentration, humans were allowed to enter the nuclear reactor buildings to begin the cool shutdown process. On the following day, the same mission was tried in Unit 2, but the PackBot could not complete it. The camera window of PackBot misted over under high humidity, because the vapor from boiled water on the basement floor did not escape from the building. Prior to the actual operations, TEPCO workers were intensively trained on remote teleoperation starting on March 24, 2011, and the scenario was verified in Unit 5, which was not dam-

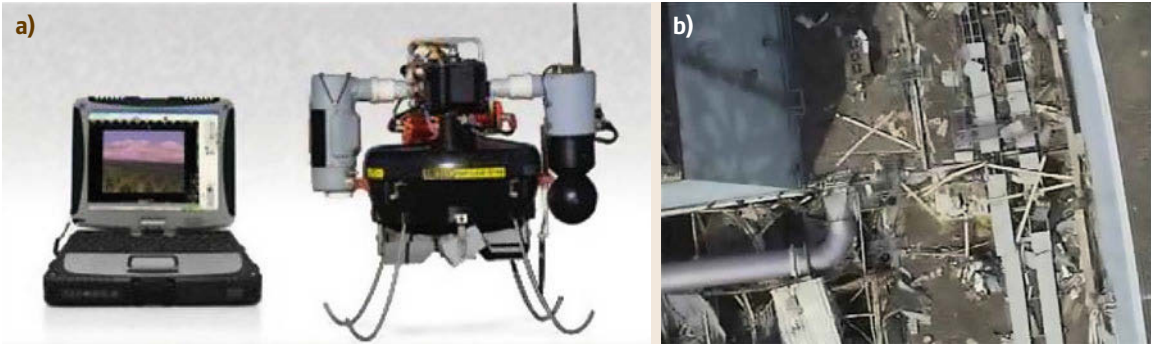


Fig.60.12a,b UAV used at Fukushima-Daiichi: (a) T-Hawk and (b) top view of nuclear reactor building of Unit 1 (photographs courtesy of TEPCO)

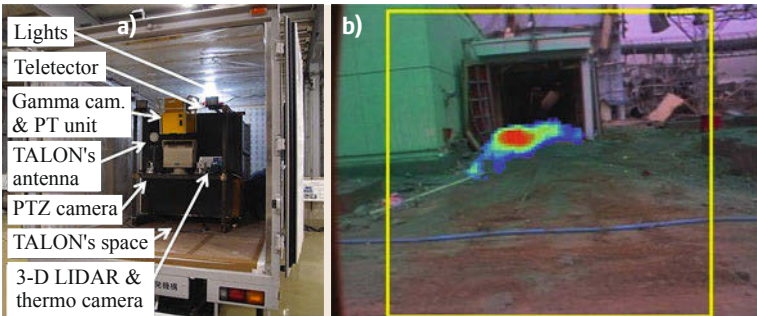


Fig.60.13a,b Gamma radiation measurement by UGVs: (a) *TEAM NIPPON* and (b) visualized radiation source by gamma camera (courtesy of JAEA)



Fig.60.14a,b Operations of PackBots in Unit 1 (courtesy of TEPCO)

aged. The PackBots continue to be used for monitoring and light tasks in the buildings.

Survey of Nuclear Reactor Buildings by Quince
The Quince robot was used in addition to the iRobot Packbots in June, 2011 (Fig. 60.14), and is now being used in cooperation with the Packbots for various missions as only Quince could climb the steps to the upper floors. Quince had been developed for CBRNE disaster response by a team from the International Rescue Sys-

tem Institute including Chiba Institute of Technology and Tohoku University. One unit of Quince was lent to TEPCO for free after radiation-proof test, wireless communication test, intensive refinement of reliability, and training exercises of operators [60.48]. Quince has been used for surveillance of the nuclear reactor building since June 24, 2011. On July 8, it entered Unit 2 and measured the dose rate on the second and third floors, then sampled dust for identification of nuclide (Fig. 60.15). On July 26, valves and pipes of a spray

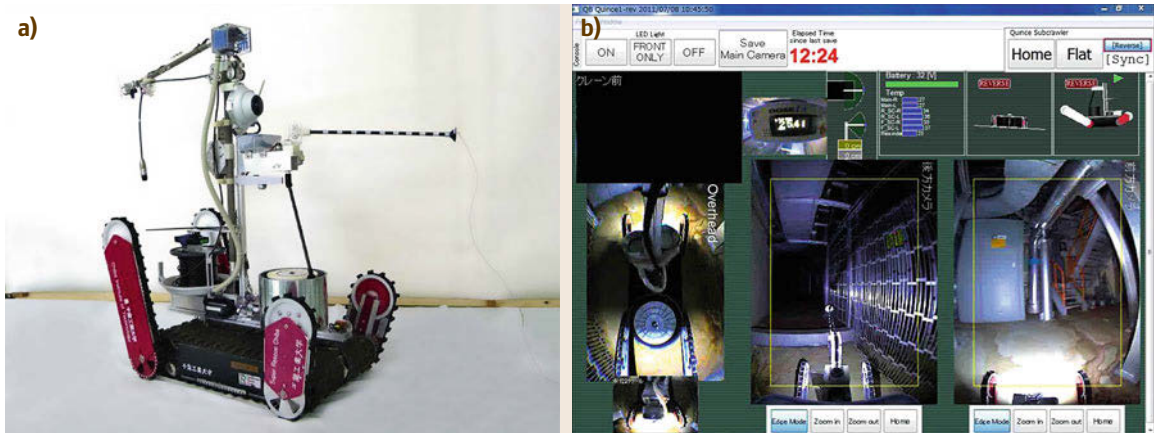


Fig.60.15a,b Quince at Fukushima: (a) robot platform and (b) its operator station image captured in the mission on July 8, 2011 (courtesy of TEPCO)

cooling system were visually inspected by the high-density camera and dose rate was measured in Unit 3. Redundant cooling system was established on the basis of these data. On October 20, Quince surveyed fully on the third floor of Unit 2, then climbed the stairs up to the fifth floor (operation floor) for monitoring. The high dose rate, condition of the crane, etc. were investigated on the high floors at first. However, it stopped on

the third floor on its return home because its communication tether was hooked and cut. If Quince had not been applied, it would have been delayed to examine situation of the upper floors, and the risk would have become higher because of late cool shutdown. Quince 2 and 3 were remodeled and lent for free of charge to TEPCO from 2012, and are used in cooperation with PackBots for various missions.

60.5 Lessons Learned, Challenges, and Novel Approaches

The experiences with disaster robotics since 2001 provide key insights into technical challenges, such as mobility, communications, sensing, control, and human factors, but also into sociotechnical issues such as training and procedures for transporting and decontaminating robots. This section highlights the general lessons learned and the fundamental problems posed in mobility for UGVs, UAVs, and UMVs, communications, control, sensors and sensing, power, human-robot interaction, multirobot team coordination, and other issues.

60.5.1 Mobility: UGVs

Mobility remains a major problem for all modalities of rescue robots, but especially for ground vehicles. The challenges for ground robots stem from the complexity of the environment, which is an unpredictable combination of vertical and horizontal elements with unknown surface characteristics and obstacles. For example, at Fukushima, the original configuration of the iRobot Packbot could not climb the steep metal staircases. In other cases, a robot could not cross a catwalk or climb

stairs due to rubble and the lack of confidence that the robot could negotiate the debris. Robots such as the Inuktun VGTV-Xtreme at the La Conchita mudslides could not handle the terrain, while the Allen-Vanguard was too heavy for vertical entry into the Midas gold mine.

The field is currently lacking any useful characterizations of rubble to facilitate better design. However, even without a complete understanding of rubble environments, it is clear that more work is needed in actuation and mechanical design as well as in algorithms that would enable the robot to adapt its mobility style to the current terrain (also known as *task shaping* [60.49]).

The state of the practice in UGVs for disasters are polymorphic tracked vehicles, with a movement toward tracked robots with manipulators (e.g., the Wolverine used for mine disasters, the robots at Fukushima) and two instances of snake-like robots (Niigata-Chuetsu earthquake, Berkman Plaza II collapse). Wheeled platforms are severely limited by the roughness of the terrain and the need to overcome obstacles, steps, ramps, but combination wheeled and tracked vehicles

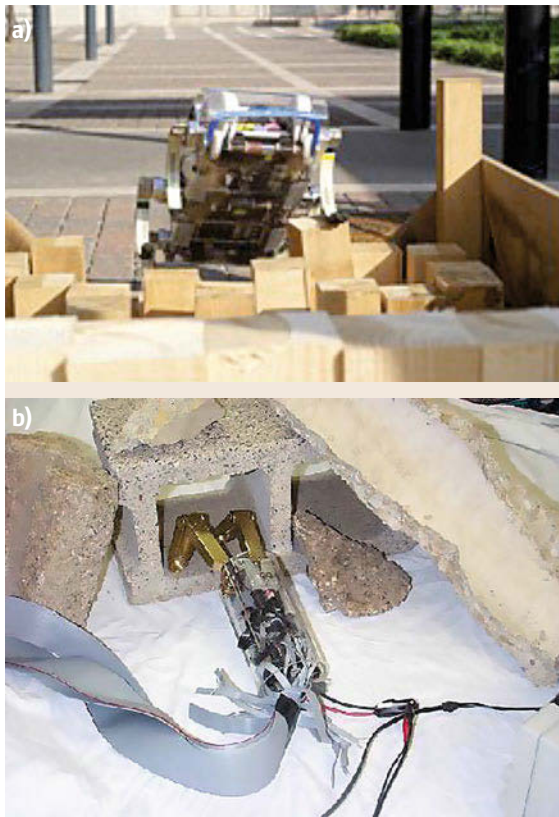


Fig. 60.16a,b Examples of legged and crawler robots. (a) Hexapod (legged) robot from the RHex project traversing a portion of the National Institute of Standards and Technology (NIST) test bed (courtesy of R. Sheh) and (b) Terminatorbot being tested in rescue test bed (courtesy of R. Voyles)

are commercially available. Basic research in legged robots (Chap. 48), wheeled robots (Chap. 49), micro/nanorobots (Chap. 27), and manipulators will benefit disaster robotics.

Free serpentine robots such as the Soryu III used at the rubble at the Niigata–Chuetsu earthquake provide a fundamentally different style of mobility, while *fixed-based* snakes can be used in tandem with a more traditional platform as a highly flexible sensor manipulator [60.50]. Examples of both types of snake robots are shown in Figs. 60.3 and 60.19.

In order to overcome the difficulties posed by unknown terrain, novel legged robots and crawler robots have been proposed. In addition, some types of crawler robots can climb walls and reach locations that would otherwise be very hard to reach. Legs are interesting because they exploit biomimetic principles. The RHex hexapod robot [60.51], proposed for search and rescue among other potential applications, is shown in

Fig. 60.16 climbing random step fields. Crawler robots such as the Terminatorbot [60.52] use their arms or legs to pull themselves through the rubble. The Terminatorbot is designed to withdraw itself into a cylinder that can be inserted through one of the small boreholes commonly drilled by responders to get through walls, then open up and begin moving. Other types of crawlers include lizard- or gecko-like robots that adhere to walls; these types are promising but have not been tested for the dusty, wet, and irregular conditions found in disasters.

Another novel concept for **UGVs** is that of *smart* tools, particularly lifts that can help stabilize collapsed structures during extrication [60.53, 54]. Extrication is one of the most time-consuming activities in rescue. Rescuers must proceed cautiously when removing rubble in order to prevent secondary collapses or slides that would further injure the survivors. Experiments suggest that roboticized lifts or shoring mechanisms would be able to sense and respond fast enough to small movements in the rubble to adaptively maintain stability [60.54].

60.5.2 Mobility: UAVs

UAVs are increasing in popularity with responders, possibly because on demand aerial access is a unique capability. Aerial vehicles, particularly helicopters, are vulnerable to wind conditions near (or in) structures and obstacles such as power lines, trees, and overhanging debris. A **UAV** at Hurricane Katrina hit a power line.

Novel ideas include a plane with the size of a person's hand that can fly indoors and planes with foldable wings, making it easier for responders to carry them. Quadrotor helicopters appear far more stable and easier to pilot; a design that balanced the larger size of a quadrotor with an appropriate payload could make **UAVs** more assessable to nonpilots. Another exciting direction is hybrid platforms that can change from fixed-wing operations, covering large distances, to rotary-wing operations, flying near or inside buildings [60.55].

60.5.3 Mobility: UMVs

Surface and underwater vehicles have to contend with swift currents and floating or submerged debris, placing significant demands on agility and control. As seen at the Tohoku Tsunami, **AUVs** could not be used due to the possibility of colliding with flotsam. Teleoperated **ROVs** can function in such conditions but have a risk of tethers becoming tangled or caught, as seen at the Tohoku Tsunami and the Hurricane Ike response.

60.5.4 Communications

Robots rely on real-time communications for teleoperation and for enabling responders to see what the robot is seeing immediately. Ground robots communicate either through a tether or via wireless radio. Aerial and surface robots are wireless, while underwater rescue robots are controlled via a tether. The communication bandwidth demands of all modalities are generally high due to the use of video imagery, and the tolerance to communications latency is low due to the control needs. In addition to communications between the tactical rescuers and their robots, it is difficult to report or transfer critical information provided by rescue robots to the strategic enterprise. Disasters typically destroy the communication infrastructure, both telephones and cellular phones, and alternatives such as satellite phones become saturated by response agencies.

Wireless communications with robots remain problematic. Operations below ground or near structures interfere with the physical propagation of radio signals. As shown in high-fidelity [USAR](#) response exercises, ad hoc wireless networks established by responders are likely to become quickly saturated, with no way of establishing priority over information. At the World Trade Center, data from the Solem robot deployed in the interior of building [WTC4](#) returned totally black frames for 1 min 40 s of the 7 min run before wireless communications were totally lost and the robot was abandoned [60.36]. In addition, many wireless robots use lossy compression algorithms to manage bandwidth, which interfere with computer vision techniques, and/or connect through insecure links, raising the possibility that news media might intercept and broadcast sensitive video of trapped victims.

Rescue robots working underground, either for [USAR](#) or mine rescue, have two alternatives to wireless communications: either operate with a tether or deploy repeaters to maintain wireless communications. Many wireless robots now can be purchased with a fiber-optic tether; however, these tethers are fragile and may break or tangle, as seen at several mine disasters. The fiber-optic tether may also tangle with the safety rope used to support the robot during vertical drops. Data for the World Trade Center deployments indicated that a dedicated person was required to manage the tether but that 54% of tether management operations were to allow the robot to reach a more favorable position or to recover the robot after its mission [60.36].

At Fukushima, outside the buildings, allocation of wireless frequencies and accommodation of communication methods were extremely difficult, and usage of some robot frequently affected the other robots. Inside the buildings, wireless communication was sometimes

unstable, and a few robots could not return. Operators always had to pay attention to radio field strength and cable tether handling.

Majority of [UGV](#) operations have used tethered robots, with the only wireless robot used at the [WTC](#) disaster being lost and the wireless [NZDF](#) robots creating significant problems with intermittent failures. Hybrid communications, in which a robot is primarily on a tether and then operates for short distances over a local wireless link before reconnecting to the tether, appear to be attractive.

A novel approach is to use other robots as repeaters, either stationary or mobile, to facilitate the establishment of communications and sensor networks. As repeaters for mobile ad hoc networks, robots on the land, sea, and air can extend the range and throughput of wireless networks [60.56]. A recent US Defense Advanced Research Projects Agency program, [LANDroids](#), developed a set of small robots that acted as mobile repeaters for a larger robot entering the interior of a structure or tunnel. Aerial vehicles are particularly attractive as they can provide larger relay ranges while providing a bird's eye view of the disaster. However, a [UAV](#) does not always have to move: a tethered blimp or kite can support a sophisticated payload with no maintenance or support for days [60.57, 58].

60.5.5 Control

Robot control can be subdivided into *platform control*, which is usually considered by control theory, and *activity control*, which generally falls under the purview of artificial intelligence. Rescue robots are challenging both for traditional control and for artificial intelligence. The high degree of mechanical complexity of all modalities and the demands of the environment present major challenges for control theory. In all report events, the robot's activity was handled by teleoperation; a human is needed to direct the robot and to perform mission sensing. The well-documented problems of manual teleoperation (Chap. 34) argue for increasing autonomy [60.59], both in terms of navigation.

Navigational autonomy has been the primary focus within the disaster robotics community and efforts generally fall into the following three categories:

- *Simultaneous localization and mapping (SLAM)*: [SLAM](#) is needed for the search and reconnaissance and mapping tasks. Whereas [SLAM](#) in office-like environments appears to be almost solved, the application of same techniques in harsh and unstructured environments turns out to be extraordinarily difficult or even impossible. One strong limitation of current mapping solutions is their inability to pro-

vide an accurate 3-D model of the environment at high data rate. For USAR such a solution has to cope with the reflection properties of debris, smoke due to fires, and the spectrum of lightning conditions. The solution also needs to be low cost in terms of required onboard CPU (central processing unit) computation and payload, due to weight and power limitations. Existing solutions rely either on automatically inclined [60.60, 61] or constantly rotating 2-D (two-dimensional) laser scanners [60.62]. In contrary to 2-D maps, which are typically generated in real time [60.63], 3-D maps are updated at low rates on the order of seconds due to the limited data rate of inclined or rotated laser scanners.

- *Exploration, planning, and path execution:* The central question in autonomous exploration is: *given what you know about the world, where should you move next to gain as much as many new information as possible?* [60.64]. Autonomous exploration can be subdivided into determining where to go next, how to plan the path to get there, and how to execute that path safely.

The primary approach to exploration is to use a frontier-based exploration algorithm is to gain new information by moving to the boundary between open space and unknown territory, denoted as *frontier*. Frontier-based exploration, either based on 2-D [60.64] or 3-D [60.65] map representations, is an efficient technique that has been successfully deployed together with SLAM techniques for exploration in NIST-like USAR arenas [60.66].

The objective of path planning in harsh environments is not necessarily to generate the shortest but the safest path. Wirth and Pellenz introduced an exploration strategy and path planner that utilizes occupancy grid maps for combining the distance transform and the obstacle transform (when planning to several frontier cells at the same time [60.67] in order to select the safest alternative consisting of target location and path to reach the target.

Most methods for motion planning in USAR are still limited to static environments that can efficiently be represented in 2-D. However, since robots operate on rough terrain that may suddenly shift it is important to consider the shape of the surrounding terrain and its potential impact when moving. Several researchers have introduced solutions with short-term planning look ahead that execute specific robot behaviors with respect to the current situation of the robot. Okada et al. introduced an autonomous controller for tracked vehicles that is based on continuous 3-D terrain scanning [60.68]. Magid et al. introduced a system for keeping the

robot maximally stable at every step of its path while allowing the vehicle to loose balance in a controlled manner for facilitating safe climbing over debris [60.69]. Sheh et al. developed a method for *behavioral cloning*, a type of learning by imitation that produces control rules that clone the skills of an expert human operator [60.70]. Dornhege et al. introduced the concept of behavior maps, which link certain robot behaviors on rough terrain such as climbing over stairs and obstacles, to structures detected from 3-D point clouds in real-time [60.71].

- *Object recognition and scene interpretation:* The search, reconnaissance and mapping, and structural inspection tasks for disaster robots would benefit from autonomy. They currently rely on humans to manually scan video feeds for signs of survivors, reconstruct the scene, identify potential hazards, and accurately comprehend the integrity of structures. To this end, Andriluka et al. evaluated various state-of-the-art techniques for vision-based victim detection from UAVs [60.72]. They concluded that by combining multiple weak models the overall detection reliability can be increased. Kleiner and Kummerle presented an approach for detecting victims based on several visual features such as body motion, skin color, and body heat [60.73]. Hahn et al. presented an approach for improving victim detection from low-cost thermal sensors by computing heat distributions while exploring an environment [60.74]. Birk et al. developed a system for recognizing humans from images taken by an infrared camera that considers plausible body shapes and postures [60.75].

60.5.6 Sensors and Sensing

Sensors, and sensing, pose the greatest mission challenge; without adequate sensing, a robot may be in an area of interest but be unable to navigate or to execute the larger mission. The physical attributes of a sensor (size, weight, and power demands) impact on whether it can be used with a particular robot platform. Currently sensors are not interchangeable between platforms; standards are needed for footprint sizes, mounting, connections, and display space.

The functionality of a sensor depends on the modality and mission [60.16]. The primary sensor missing from all robot modalities operating outside of water is a miniature range sensor. With a miniature range sensor, the success in localization and mapping seen with larger robots would be transferable to rescue robots. The sensor payloads for other missions depend on those applications; however, two sensor needs for USAR are

particularly noteworthy. One is a detector that can perceive victims obscured by rubble; current radars have not been reliable in mixed rubble. Another needed sensor is one that can tell if a victim is unconscious but alive without touching the victim. A robot may be able to see a victim, yet not be able to crawl to the victim and make contact or scrape away enough dirt or clothing to take a pulse. Stand-off detectors such as millimeter-wave radars and gas detectors appear promising but have not been validated at this time.

Smaller, better sensors are not sufficient; improvements in sensing algorithms are also needed. At this time, humans are expected to interpret all sensing data manually in real time. This is a daunting task for many reasons. Human performance is handicapped by physiological factors introduced by sensing through a computer display (also known as computer mediation), the location of sensors at viewpoints low to the ground, generally restricted fields of view, and fatigue. The modality output itself may also be nonintuitive, such as ground-penetrating radar. However, autonomous detection and general scene interpretation is considered well beyond the capabilities of computer vision. This presents a case where neither the human nor the computer can accomplish the perceptual task reliably and argues for investigation into human–computer cooperative techniques for perception. Algorithms that enhance the image for human inspection, supplement depth perception, or cue interesting areas are within the reach of computer vision.

60.5.7 Power

The robot modality and mission poses distinct challenges for power, although only one robot, the [NZDF](#) robot at the Pike River mine, has caused a failure. In general, battery power is preferred over internal combustion because of the logistics difficulties in transporting flammable liquids. While the requirements of each rescue robot application is largely unknown, a partial understanding is emerging of the power profile. For example, the operation tempo of a ground vehicle operating underground is on the order of 3–4 runs, each around 20 min in duration, over a 12–14 h shift, with the robot kept on hot standby for the majority of the shift. Rotary-wing aerial vehicles for tactical reconnaissance and structural inspection show an operations tempo of 5–8 min per face of a building, while fixed-wing vehicles are airborne for less than 20 min. Other rescue missions, such as wilderness search and rescue, will have different requirements but the need for batteries over internal combustion and for determining the power profile is the same.

60.5.8 Manipulation

Manipulation has been required for mine remediation (e.g., DR#1 and McClane Canyon mines) and at the Fukushima nuclear accident, but overall manipulation has failed in at least one task per mission. Furthermore, manipulation is almost always time consuming as all reported instances have been teleoperated. Robots with manipulators (such as that seen in [Fig. 60.17](#)) extend the capabilities of ground vehicles by allowing the robot to sample the environment, interact with survivors, move light obstructions, and add unique camera viewpoints. However, the manipulator extends the volume of the robot, impacting navigation. The arm is often at risk of being damaged in confined spaces being hitting on overhanging rubble. Manipulators also add to the control and mechanical complexity of the robot.



Fig. 60.17a,b Examples of tracked robots with manipulator arms that have been used for disasters or rescue competitions. **(a)** View from Foster-Miller Talon at the WTC of its arm (courtesy of [CRASAR](#)) and **(b)** teleMAX by Telerob at the Rescue Robotics Camp (courtesy of R. Sheh)

60.5.9 Human–Robot Interaction (HRI)

According to the analysis by *Murphy* [60.22], over 50% of the robot failures during a disaster are due to human error, which emphasizes the importance of human–robot interaction. For the purposes of this chapter, **HRI** concerns fall into five topics: ergonomics, system design, human–robot ratio, situation awareness, and training.

One aspect of **HRI** is ergonomics. The Fukushima nuclear accident highlighted how personal protection equipment (e.g., full-face mask and rubbery gloves) precluded workers from performing delicate work and efficient task execution.

Another aspect of **HRI** is the larger system design. At the Fukushima nuclear accident, workers had to carry the robots to the point of entry; this sometimes increased the total radiation exposure of workers, which was clearly not the purpose of the robot. The inability to transport certain robots caused them to be excluded from the World Trade Center disaster.

The number of operators per robot has been the subject of debate, though *Murphy* and *Burke* in [60.76] offer a formula based on their comprehensive field studies for computing the baseline human-to-robot ratio

$$N_{\text{humans}} = N_{\text{vehicles}} + N_{\text{payloads}} + 1.$$

The idea is to then justify why a smaller ratio would not increase unacceptable risk to the mission. For example, a **UGV** often does not need a safety officer, while a **UAV** does under most regulations. One way to decrease the number of people is to reduce their workload, such as by increasing the navigational autonomy from normal operations. However, *Murphy* and *Burke* document that if the unmanned system encounters a problem and returns control to the operator, the operator is unlikely to be able to react fast enough to avoid a crash, collision, or severing of a tether. This problem has been documented in aviation safety with initial problems with auto-pilots, where it is generally referred to as the *human out of the loop control* (**OOTL**) problem. The **OOTL** problem should not be interpreted as discouraging autonomy but rather encouraging a more comprehensive consideration of how autonomy will be handled in all conditions, not just normal operations.

Related to the number of operators is how well they can maintain situation awareness. Situation awareness is defined by *Endsley* in [60.77] as

the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.

Drury et al. [60.78] have defined types of situation awareness within search and rescue based on an analysis of RoboCup rescue tasks, while *Casper* and *Murphy* [60.79] and *Burke* et al. [60.80] have examined operator situation awareness in technology insertions. User interfaces are a key component in facilitating situation awareness. In rescue robotics, user interfaces are generally primitive and work through the operator's visual channel to provide robot, task, and situation awareness of the state of the robot, task progress, and the general operational environment. To highlight the importance of user interfaces, one robot at the World Trade Center was rejected because of the complexity of its interface [60.36]. While the user interface for fieldable rescue robots primarily display the video output from the robot, experiences from RoboCup rescue suggest that a good interface will both facilitate commanding the robot (inputs) and will provide three types of information (outputs):

- The robot's perspective: camera view(s) from the robot's current position, plus any environmental perceptions that enhance the general impression of telepresence
- Sensor and status information: critical information about the robot's internal state and its external sensors
- If possible, a map: a bird's eye view of the robot situated in the local environment.

The Fukushima nuclear accident illustrated the importance of training, as training of operators with using simulated mockups took over a month. The current state of the practice is for responders to receive training from the robot manufacturer on how to operate and maintain the robot, ignoring concepts of operations for actual scenarios. Training is a related issue in human–robot interaction [60.81]. Rescue workers have limited time compared with military operations to learn about robots and few opportunities to practice. While a bomb squad or special weapons and tactics team for law enforcement may be called out several times each month, a rescue team may be called out only a few times each year. For the near future, rescue workers may not have had prior training or experience with a robot prior to the disaster and be expected to use prototypes with only *hasty* training.

60.5.10 Multirobot Team Coordination

Multirobot teams of robots that cooperate with each other or work on the same objective have already been used or demonstrated for response and recovery activities at Hurricane Wilma (**UMV-UAV**) [60.24], the Tohoku tsunami (**UMV-UMV**) [60.31], and the To-

hoku earthquake (UAV-UGV) [60.30]. These have all been heterogeneous teams though homogeneous teams have been entered at the RoboCup rescue competition [60.82]. Only one of the three deployed teams was explicitly coordinated, where a Quince robot carried a Pelican UAV at the Tohoku earthquake and conducted cooperative mapping of the interior of a damaged building [60.30]. The current research approach to teams is focusing on adopting techniques from artificial intelligence for either centralized or distributed coordination.

Multirobot teams not only offer the possibility to field diverse capabilities, they also exhibit increased robustness due to redundancy, and superior performance by parallel task execution [60.83]. This latter aspect is as important as the first one, since the time to complete a rescue mission is of vital importance. For example, one fundamental problem when searching for survivors is to efficiently coordinate a team performing space exploration. However, the IRS-CRASAR team at the Tohoku tsunami response uncovered implicit assumptions about parallel task execution that limited performance [60.31]. The coordination of several autonomous units in search and rescue operations still represents an open issue. One reason is the fact that the higher number of degrees of freedom imposed by the robot team requires a larger number of trained human operators, which in turn makes the deployment during a rescue mission more complicated. Certainly, the number of required operators also depends on the quality of autonomous perception and decision-making of each single system. Therefore, in order to reduce the human-to-robot ratio in the field, autonomous capabilities as well as autonomous methods facilitating team coordination are needed. There are several existing techniques for team coordination in USAR, which can generally be separated into centralized and decentralized approaches.

There are three novel types of teams being pursued for disaster robotics. One type is swarms. Researchers such as [60.84] have discussed the possibility of using cost-effective, insect-sized robots to penetrate deep within a pancake building collapse and then signal the presence of a victim. One of the key features of swarm approaches is that they can scale up easily. The insect swarm scenario leaves hard problems like control, sensing payloads, localization of the victim, and communications to the imagination, but is certainly a worthy concept. However, some of the search algorithms used by insects may be adapted to single robots, for example, win-shift win-stay sampling exhibited by bees may be useful for search [60.85]. A second type of team, similar to swarms, is motes, where aerial vehicles that drop intelligent sensors called motes.

A third type of team is a hybrid robot-animal team, where search dogs carry roboticized cameras (dog-cams) [60.86] or wiring rats with controllers. Attaching cameras to search dogs has been explored for several years and such a system was used at the World Trade Center. The concept does not compete with robots, as robots are used to enter places canines cannot. The canine team handlers have generally objected to dog-cams because the cameras and communications gear interfere with the dog's mobility, pose the hazard of snagging, and the dog cannot be readily commanded to stop at points of interest beyond the line-of-sight of the handler (dogs use visual cues as commands, more than audio). However, there is less objection to placing nodes in a rat's brain to stimulate and drive the rat into a void while carrying a camera or other sensors [60.87]. The motivation for a robot rat stems in part from the rat's mobility and relative low value. While the technical feasibility of a robot rat may be within reason, assuming advances in wireless communications, the response community has been lukewarm toward the idea [60.88]. Unlike rats, robots can be kept in storage for years and can penetrate through pockets of fire or areas with no oxygen. A robot rat has all of the limitations of dog, including the problem of a handler becoming too emotionally attached, and is likely to scare a trapped survivor just as much as the other rats that swarm a disaster. The conventional wisdom is that, if the sensors, wireless, and power systems can be miniaturized and operate reliably enough to control a rat deep within rubble, those systems will enable responders and robots to work without the rats.

60.5.11 Other Issues

In addition to the challenges by the functional subsystems of a robot, three other issues should be considered.

Robots must be reliable. As noted in the discussions of the Pike River mine explosion and the Fukushima nuclear accident, *failure of a robot can obstruct the mission execution or cause it to completely fail*. A robot failing not only means the mission did not get performed, but could prevent other robots from carrying out the mission. For example, a robot getting stuck on the stairs would pose a navigational hazard to other robots or to workers in bulky safety gear. Such risk has to be minimized by thorough analysis and preparation beforehand.

Robots must be suitable for the environment. In at least two mine disasters, robots could not be used because they were not explosion proof – yet needed to be used in an explosive atmosphere. At Fukushima, robot operators had to be concerned with potential

damage of semiconductors by total dose of radiation, which could affect not only CPU and image sensors but also various components using semiconductors such as engine, battery, etc. Monitoring of the total dose using a dosimeter was necessary.

Robots must be decontaminated. Radiation contamination at Fukushima was a serious issue because it

caused radiation exposure of workers in maintenance and battery exchange. However, UGVs at the World Trade Center collapse were exposed to raw sewage and body fluids. Decontamination has been discussed in standardization procedures but few platforms are built to be completely cleaned or to be easily cleaned without exposing the human.

60.6 Evaluation

Disaster robotics is still an emerging field and methods for evaluating a rescue robot or the larger mixed human–robot system are still forming. *Murphy* in [60.22] provides an analysis of the performance of disaster robots at 34 events. Evaluation is largely centered around the US government National Institute of Standards and Technology (NIST) efforts to standardize rescue robots for adoption by US responders via originally a standard test course and more recently a set of standard test methods. Each standard test method is an inexpensive, reproducible prop that tests a single capability; for example, Fig. 60.18 shows a prop designed to test a robot's ability to traverse rough terrain represented by a wooden *step field*. The standard test course and methods are duplicated via the USARsim computer simulation, and at least two sites, NERVE and SWRI, have physical testbeds consisting of the NIST standard test methods – though other physical testbeds such as Disaster City exist. The test course and methods have been used since the late 1990s for the RoboCup rescue and AAI mobile robot competitions. This effort is being conducted through ASTM and thus, even though it is largely driven by the US, will likely result in an international standard that may be adopted by other countries.

60.6.1 Computer Simulations for Rescue Robotics

Computer simulations provide a low-cost mechanism to explore the larger behavior of a robot or system. Generally, computer simulations provide high fidelity for testing software execution, but their physical fidelity depends on the physics engine. Simulating sensors and the complex environments produced by a disaster is difficult and is rarely accurate enough to test perceptual algorithms. At the time of writing, two readily available computer simulations exist for exploring the strategic and tactical applications of rescue robots within the RoboCup rescue framework [60.89], the *RoboCup rescue simulation project* [60.90], and *USARSim* [60.91]. These simulations are well understood, accepted, open-

source, and free; as such, they should be useful for most researchers or practitioners interested in ground-based rescue robotics.

The RoboCup rescue simulation project is used in the RoboCup rescue simulation league to study agent-based approaches to strategic planning for the disaster response. The simulator assumes a strong centralized response capability that is not necessarily the case for all countries or regions; the United States, for example, relies on a highly distributed organization that obviates many centralized coordination schemes. Although the simulation is focused on strategic decision making, particularly dynamic resource allocation, it does support the examination of how robot resources might be allocated during a disaster and how data from a robot might be propagated through a system. It permits the simulation of monitoring of disaster damage from reports by humans, distributed sensors, and robots and can simulate complex interactions such as telemedicine.

USARSim is a computer simulation developed by the University of Pittsburgh for physical robot simulation in disaster situations [60.91]. The simulation replicates the NIST standard test bed for search and rescue and permits efficient prototyping and testing of robot design and most aspects of control software. It uses Unreal game engine for handling physics and graphics, and virtual robots have capability of sensing (image, laser range finder, etc.) and actuation (wheel, motor, etc.) with data processing (image recognition, SLAM, etc.) in artificial environments. In 2006, the RoboCup rescue competition created a simulation league using this environment.

60.6.2 Physical Test Beds

Physical test beds provide a more realistic venue than a computer simulation for evaluating rescue robots, but may not be available to researchers, too expensive to use or to travel to, or not adequately capture some key aspect of a disaster. Physical test beds generally fall into three categories: *test beds developed for the fire rescue*



Fig. 60.18a–c View of the [NIST](#) standard test bed for search and rescue used by RoboCup Rescue. **(a)** View of overall test bed, **(b)** dummy representing a victim, and **(c)** a step field challenging robot mobility (courtesy [NIST](#))

community, test beds developed for the robotics community, and the [NIST](#) standard test bed for search and rescue.

Fire rescue training test beds occur throughout the world and are used to train human firefighters, rescue specialists, and canine teams under highly realistic conditions. The Texas A&M Engineering Extension Service's Disaster City complex has 52 ac devoted to



Fig. 60.19 A [CMU](#) (Carnegie Mellon University) fixed-base snake being tested at a facility in California (courtesy H. Choset)

representative structural collapses, ranging from multi-story commercial building to wooden housing. Disaster City is the site for the [NIST](#) Response Robot Evaluation Exercises. The [NASA](#) Ames Research Center's Disaster Assistance Response Team facility at Moffett Field has hosted several events as well. In general, fire rescue test beds are constructed from construction and sewer debris, can introduce smoke and some simulants, and pose challenging mobility conditions, but vary in terms of fidelity. In many test beds, the density of the debris does not contain the actual amount of metals in a real collapse. This can lead to optimistic reports of success of sensors and wireless communication devices. The test beds, being designed for human training, do not replicate the conditions under which a ground robot would be used. The terrain is generally on the exterior of the rubble and does not exercise the robot in confined or vertical spaces. Depending on the size of the facility, the test bed may or may not be suitable for evaluating [UAV](#)s. An example of a fire-training test bed appeared earlier in [Fig. 60.19](#).

Physical testbeds for the robotics community such as the New England Robotics Validation and Experimentation ([NERVE](#)) Center at the University of Massachusetts Lowell, and the facilities at the Southwest Research Institute ([SWRI](#)) in San Antonio, Texas, incorporate both general test courses for robots and the [NIST](#) standard methods.

Perhaps the most influential physical simulation for researchers is the RoboCup rescue physical league which uses the [NIST](#) standard test bed for search and rescue, shown in [Fig. 60.18](#). This competition started in 2001 [60.92] and has more than 40 team entries every year from all over the world. The RoboCup rescue physical league scores robot performance in terms of mobility, mapping, situation awareness, sensing, shared autonomy, etc. A robot or robot team competes in one

of three arenas which simulate disaster situations at the annual RoboCup world competition. The mission of the robot teams is to collect victim information (existence, state, and location) by sensor fusion of vital signals (heat, shape, color, motion, sound, CO₂, etc.) and report a map of victims in disaster space so that responders can efficiently arrive at the victim for rescue. In addition to the arenas, the competition and test bed contain individual skill test stations, for example, in order to test mobility, robots must traverse a random step field made of wood. The test bed was designed to be portable and reasonably inexpensive and several locations around the world have set up duplicates. As a result of the constraints of cost and portability, the test bed is not fully representative of actual disaster physical conditions and does not test the operating conditions for the human teams.

60.6.3 Standards Activity

Standards for rescue robots and systems are being generated at the time of writing. The E54.08 subcommittee on operational equipment within the E54 Homeland Security application committee of ASTM International started developing an urban search and rescue (USAR) robot performance standard with the National Institute of Standards and Technology (NIST) as a US Department of Homeland Security (DHS) program from 2005 to 2010. It plans to cover sensing, mobility, navigation, planning, integration, and operator control in order to ensure that the robots can meet operational requirements under the extreme conditions of rescue. The standards will consist of performance measures that encompass basic functionality, adequacy and appropriateness for the task, interoperability, efficiency, and sustainability. The components of the robot systems include platforms, sensors, operator interfaces, software, computational models and analyses, communication, and information. Development of requirements, guide-

lines, performance metrics, test methods, certification, reassessment, and training procedures is planned.

60.6.4 Evaluation

Evaluation of rescue robots is difficult not only because of the diversity of platforms and missions but also because each disaster is truly different. In addition, robots are part of a human-centric system: they are operated by humans in order to provide information to humans. Evaluation of the performance of a rescue robot system at an actual disaster is currently ad hoc. No computer or physical simulation for predicting the performance of robots and humans in a disaster has been validated; indeed, there is little argument that simulations are far easier than a real response. The difficulties of simulation are exacerbated by the differences between disasters. For example, the World Trade Center was unique in terms of the large amount of steel and the density of the collapsed material, while earthquakes and hurricanes are different from terrorist events.

Metrics for measuring performance remain a worthwhile quest. Quantitative metrics, such as the number of survivors or remains found, do not capture the value of a robot in establishing that there are no survivors in a particular area. Performance metrics from psychology and industrial engineering are only now beginning to be applied. These methods require enhanced computer and full-scale simulations in order to collect data. Data collection on human and overall system performance during a disaster has been done through ethnographic observations and are now moving to direct observations of situation awareness during demonstrations [60.80, 93]. Direct data collection during a disaster may not be possible as methods may interfere with performance (and therefore be unreasonable, if not unethical) and arouse fears by operators of *Big Brother* and being held liable for any errors in operation.

60.7 Conclusions and Further Reading

Rescue robots are making the transition from an interesting idea to an integral part of emergency response. Aerial and ground robots have captured most of the attention, especially for disaster response, but water-based vehicles (both surface and underwater) are proving useful as well. Rescue robots present challenges in all major subsystems (mobility, communications, control, sensors, and power) as well as in human-robot interaction. In terms of size, man-portable and man-packable systems are the most pop-

ular because of their reduced logistics burden, but the size of the platforms exacerbates the need for miniaturized sensors and processors. Wireless communications remains a major problem. While recent deployments have relied on polymorphic tracked vehicles, researchers are investigating miniature planes and helicopters along with new ground robots designs, particularly biomimetic. Research is also exploring alternative concepts of operations and user interfaces. Standards are currently under development and this

will help accelerate the adoption of rescue robots. The annual IEEE (Institute of Electrical and Electronics Engineers) International Symposium on Safety, Se-

curity and Rescue Robotics is currently the primary conference and clearinghouse for research in rescue robotics.

Video-References

-  **VIDEO 140** Assistive mapping during teleoperation available from <http://handbookofrobotics.org/view-chapter/60/videodetails/140>

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61. Robot Surveillance and Security

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This chapter introduces the foundation for surveillance and security robots for multiple military and civilian applications. The key environmental domains are mobile robots for ground, aerial, surface water, and underwater applications. Surveillance literally means *to watch from above*, while surveillance robots are used to monitor the behavior, activities, and other changing information that are gathered for the general purpose of managing, directing, or protecting one's assets or position. In a practical sense, the term surveillance is taken to mean *the act of observation from a distance*, and security robots are commonly used to protect and safeguard a location, some valuable assets, or personal against danger, damage, loss, and crime. Surveillance is a proactive operation, while security robots are a defensive operation. The construction of each type of robot is similar in nature with a mobility component, sensor payload, communication system, and an operator control station.

After introducing the major robot components, this chapter focuses on the various applications. More specifically, Sect. 61.3 discusses the enabling technologies of mobile robot navigation, various payload sensors used for surveillance or security applications, target detection and tracking algorithms, and the operator's robot control console for human-machine interface (HMI). Section 61.4 presents selected research activities relevant to

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surveillance and security, including automatic data processing of the payload sensors, automatic monitoring of human activities, facial recognition, and collaborative automatic target recognition (ATR). Finally, Sect. 61.5 discusses future directions in robot surveillance and security, giving some conclusions and followed by references.

61.1 Overview

Surveillance robots and Security robots are tactically similar in design, but their specific purposes are very different. The surveillance robot uses its payload to map or search an area, while the security robot is used to protect and safeguard an asset such as the prime-

ter of an airport. In comparing these two categories of robots, the difference in operations would be analogous to comparing surveillance to a global problem and security to a local problem. Operationally, the surveillance robot collects data with its electronic payload



Fig. 61.1a–d Examples of surveillance and security robots. (a) Aerial-General Atomics Predator, (b) ground-QinetiQ TALON, (c) ground-General Dynamics MDARS-E, and (d) surface water-Elbit Stingray

(also known as the robot's external sensor) and relays the raw data back to its control station or preprocesses the data with other information such as geographic information system (GIS) data and relays that information to an exploitation element. Eventually as more autonomy is integrated into the vehicle, the robot will be able to plan its own paths and point its sensor with minimal human intervention. The quality of surveillance is a function of target range, the amount of target clutter, sensor resolution, and its probability of detection of a target. Security robot operations consist of a mobile robot patrolling a defined area (or perimeter), detecting an intruder or suspicious activities, and initiating a response. A security robot can conduct predefined or random patrols, and automatically perform surveillance tasks such as checking for intruders or assessing the status of the perimeter defenses. Input from the operator is required only if an intruder is detected or the robot encounters a situation it is not programmed to handle. Once contact is made, the operator is able to see, hear, and talk to the intruder. If the intruder tries to avoid the robot, the intruder can track them with its onboard sensor and maneuver for the robot to follow the suspected intruder. Search and Rescue Robotics (Chap. 58) uses some aspects of surveillance due to the potentially wide area to be searched and the actions of security where upon detection, an action is required.

The basic security robot [61.1] can be as simple as a fixed-sensor, mounted up high and able to pan and tilt without being able to move around. There are concepts to use a low-cost sensor (to sense motion,

detect vibration, or break a sensor-beam) in order to cue a more sophisticated second sensor (e.g., radar or video) for confirmation. Depending on the complexity of the security system, the fixed sensor can alert a mobile robot, which can otherwise be defeated by just waiting for the robot to pass. A combination of fixed and mobile assets can be a very robust solution system. Again, the nominal robot configurations are still similar (Fig. 61.1): robot with sensor payload, an operator station, and a communication system that links the robot with its control station [61.2–5]. In some cases, there may be two distinct control stations, one for controlling the robot and one for handling the payload data as seen on military drones. A surveillance robot can be more data intensive as compared to the security robot which often performs in a structured environment and has a narrower data load to process. Central to both applications are the robot or robots, and the control station. Robot surveillance is in greater use today due to the war in the Middle East (Iraq and Afghanistan) with the proliferation of military drones. The majority of unmanned aerial vehicles (UAVs) are controlled via teleoperation or by flying automatically through waypoints. UAVs are now commonplace in the military, and slowly making inroads into the commercial sector with applications in agriculture, forest fire mapping, and weather analysis. The next technological step forward for surveillance robots is autonomous operations and multi-vehicle coordination (i. e., swarming). Robot security is less developed with some on-going research programs within the military, and a few commercial options available on the market today. Early mobile robot companies in the 1980s were formed to address these same security concerns such as Cybermotion Inc. and Denning Mobile Robotics, Inc. but did not survive over time. The next logical progression for robot security is to bring the costs down to make the systems more viable, reduce false-positives to make detection reliable, and take unnecessary personnel out of daily control through the careful insertion of automatic and autonomous technologies.

There are some fundamental issues that need to be addressed in the design and development of the surveillance or security robot system. For example, each specific applications will dictate if surveillance occurs indoors or outdoors, and similarly for indoor or outdoor security, such that sensors are different to address weather or lighting concerns. There are numerous applications for either case, and will impact the type of mobility chosen, and the type of sensors used for monitoring and detection. As noted earlier, robot surveillance typically requires mobility; while security robots can be either stationary or mobile. In the later, the environment is known (or classified as being struc-

tured) with set vehicle trajectories defined a priori in the majority of applications. Some robot security applications may involve a combination of both fixed and mobile robots depending on the size of the facility or building. The first issue to contend with is having to select between teleoperated and autonomous control of the robot. There is a scenario to start with a teleoper-

ated system that can eventually evolve toward a more capable automatic or autonomous capability. However, experience has shown that this upgrade seldom occurs naturally without planning and when the capability does mature, it will require large software block upgrades and the hardware will normally require upgrading also to increase overall capability.

61.2 Application Domains

Surveillance and security robot designs begin by first understanding its intended operational environment, and simultaneously designing for data collection or various protection schemas. The typical surveillance robot requires a surveillance payload, while a security robot integrates a security sensor. This sensor suite is in addition to a navigation sensor suite required by the robot for mobility. There may be an opportunity to use the same sensor for both navigation and payload, but this option is very isolated due to disparate range and resolution requirements. Since there are two different sensors, some coordination is required between mobility of the robot and the desired viewing angle of the payload sensor.

Surveillance and security robots (Fig. 61.2) can be found in all the normal environments (e.g., aerial, ground, surface water, underwater, or space), for example by watching from above from either space or from an aerial elevation. Robots patrols are found in ground [61.6, 7] and aerial applications:

- **Aerial Domain:** The majority of long distance aerial applications utilize fixed wing vehicles flying at a set altitude and monitoring large surface areas. Aerial vehicles come in all sizes from full-size platforms that are the size of passenger jetliners to small quad-rotors, vertical take-off and landing vehicles, and microflapping wing aircraft as described in Chap. 50. Electro-optical (EO), infrared (IR), or synthetic aperture radar (SAR) are sensors nominally used to collect surveillance data. A fixed-wing aircraft can also be used for security, but rotorcraft platforms (especially a quad-rotor) are the mobility of choice for its hovering capability as shown in  VIDEO 554. The weakness in rotorcraft platforms is its weight limitations, e.g., sensor payload weight and vehicle flight time. Key aerial design constraints are Reynolds number, Lift-to-drag (L/D) ratio of the wings, Breguet range analysis, vehicle endurance, and vehicle aspect-ratios. Communications between aircraft and ground control station is direct line-of-sight or over-the-horizon using satellites or other

UAVs when functioning as a communication repeater.

- **Ground Domain:** Ground vehicles are either custom-designed or based on retro-fitting an existing commercial or military vehicle. They come in all sizes from automobile-size to desk-size and shoebox-size such as the Dragon Runner as described in Chap. 48 and potentially walking as described in Chap. 65. An EO, IR, or range finder is used to collect surveillance data. For robot security, a similar EO, IR, lidar, or range finder sensors are often used as can be seen in  VIDEO 677. Key ground design constraints are types of vehicle steering modes, type of propulsion (wheeled, track, legged, or hybrid) system, range, suspension, and draw-bar pull performance. The standard packet-radio used for communications is bandwidth limited, thus ground robots would benefit from and automatic RSTA capability (RSTA: reconnaissance, surveillance, and target acquisition).
- **Surface Water Domain:** Surface vehicles are either custom-designed, or based on retro-fitting an existing boat such as a rigid hull inflatable boat (RHIB). They vary in sizes from a small jet ski to an 11 m RHIB. Surface water robots used for surveillance and security are in its infancy. Potentially, a radar can be used to conduct surveillance, data and for robot security, a combination of radar and EO sensors are envisioned. Key surface water design constraints are vehicle speed, range, and draft and beam dimensions for flotation. Surface navigation requires GPS for localization when visual techniques are ineffective and when water features are indistinguishable.
- **Underwater Domain:** Unmanned underwater vehicles (UUVs) vary in size from man-portable lightweight platforms to large diameter vehicles of over 10 m in length. The larger vehicles have an advantage in terms of endurance and sensor payload weight capacity as described in Chap. 51. Sonar is the payload sensor (sidescan or other) and is used to collect surveillance and support navigation data.



Fig.61.2a–e Wide ranging operational environments: (a) Air-Tacocopter, (b) Ground-Asian Forum for Corrections' Robo-Guard, (c) Underwater-Bluefin 9, (d) Surface water-Rafael Protector, and (e) Space-Ball Aerospace SBSS Satellite (SBSS: space based space surveillance)

The majority of operational **UUV**s are tethered, but untethered vehicles have a larger presence in the research world (better known as autonomous underwater vehicles or **AUV**s). Key underwater design constraints are Reynolds Number, buoyancy, endurance, pressure, and being tethered or untethered. Secure underwater communications is an issue for connecting the robot with its operators.

- **Space Domain:** Spacecraft by nature are considered robotic. There is a combination of onboard automation and a mix of commanding from the ground during critical events. Surveillance spacecraft range in size from microsatellites (50–100 kg) to traditional (approximately 15 000 kg) surveillance-size spacecraft, and the typical payload sensors include high-definition cameras and **SAR**. Security satellites are used to protect assets on the ground, and having the ability to detect and track objects from space is crucial to preventing threats, whether real or accidental.

Key spacecraft design constraints are weight, power usage, thermal cycling, surviving launch loads, and operating at cryogenic temperatures.

As shown, there is a wide range of surveillance and security robots in multiple domains. Domains have specific individual environmental concerns. A domain not discussed is underground, as experienced with mining applications or the surveillance of caves with the iRobot 110 FirstLook or other small unmanned ground vehicle. It is clear with all of these robots that there is a navigational component and a payload/sensor component. Coordination between navigating and sensing for surveillance and security is of interest to robotic researchers. As noted earlier, the dominant robot applications are aerial surveillance, which covers large surface areas by a fast moving aircraft, and ground (and surface water) vehicles for security that move slower on predefined paths.

61.3 Enabling Technologies

Robot surveillance and Security requires sensing, data collection, mobility (optional), navigation, communication, control, computer vision, and having a preplanned response (i.e., using deterrence) as a security action. Acceptable responses can be as benign as alerting a human guard, to immobilizing the threat, or potentially incorporating a weapon to remove the threat. There are many relevant technologies needed for this application. In this section, we will discuss the selected enabling technologies of: mobile navigation, payload sensors, applicable algorithms, and the human–robot interface at the operator control console.

61.3.1 Mobile Navigation

Teleoperated mobility is a well-developed technology as long as the communication bandwidth is available between the assets. For fast moving surveillance robots such as large aerial platforms [61.8], teleoperation is an

option but today's technology is to fly via **GPS** waypoints. Waypoints are sets of coordinates that identify a point in physical space such as *X*, *Y*, *Z*, or longitude, latitude, and altitude. Navigation systems such as **GPS** (or other radio triangulation systems, i.e., Loran or Kaman) are used to maneuver the aircraft to fly-over or fly-by the waypoints. Fly-by waypoints are used when an aircraft should begin a turn to its next course prior to reaching the waypoint separating the two route segments, and fly-over waypoints are used when the aircraft must fly over the point prior and start its turn. In practice, the aerial robot will fly directly overhead of a fly-over waypoint, and can miss a fly-by waypoint by a couple of miles due to a practice called *cutting the corner*. The critical phases for all **UAV**s are during its launch and at its recovery, and would benefit from emerging sense-and-avoid technologies. For underwater applications where **GPS** is not accessible unless the platform surfaces periodically, the robot [61.9] navi-

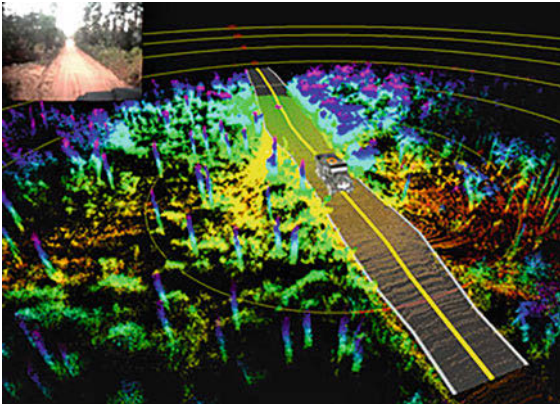


Fig. 61.3 Autonomous navigation in outdoor terrain (courtesy of Carnegie Mellon University National Robotic Engineering Center)

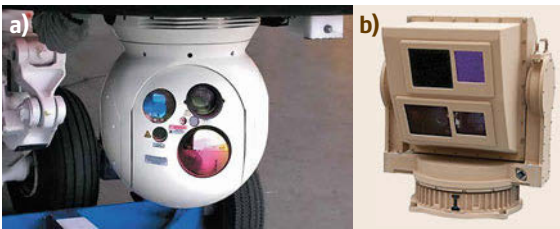


Fig. 61.4a,b Typical EO sensors: (a) UAV EO gimbal sensor suite (courtesy of forward looking infrared (FLIR) systems) and (b) (UGV) EO/IR gimbal sensor suite (courtesy of L3 – Wescam)

gates through the use of dead reckoning with frequent landmark corrections.

For unknown and unstructured environments, teleoperation for security robots is the state of practice for aerial, ground, and surface water applications. When there is a setup period and the path is known a priori, as within a *structured* environment, preplanned paths can be incorporated. For a more advanced ground robot, autonomous navigation [61.10] is being researched and developed (predominantly in the outdoor environment). Benchmarks for autonomous navigation (Fig. 61.3) in complex, outdoor environments were established on the DARPA PerceptOR and LAGR programs (LAGR: learning applied to ground robots; PerceptOR: perceptions for off-road robotics). Refer to Chap. 35 for techniques that contribute to an autonomous navigation capability.

61.3.2 Payload Sensors

The end-user for surveillance data are the commanders, decision makers, analysts, targeteers, weaponeers (when a response is separate from the UAV), and

cartographers. The information sought is timeliness, synoptic coverage, sensor resolution, sensor accuracy, interior details, and the differing elevations. Some basic payload definitions are:

- Real-time: information arrives after the event at the speed of electrons.
- Near Real-time: information arrives between real time and 20 min after the event.
- Accuracy: level of agreement with standard map datum.
- Precision: fineness of resolution to which measurements can be made.
- Field of View: angular area observed by a fixed (nonscanning) sensor.
- Field of Regard: angular area observed by a scanning sensor.

Surveillance sensor options include passive imaging [61.11], active imaging, and nonimaging sensors. Film and EO sensors are passive imaging. An example of passive imaging on the DARPA UGV Demo II program is shown in [VIDEO 679](#). In addition to EO, IR optical sensors often accompany its daylight counterpart in order to be also able to see in darkness (commonly denoted as EO/IR). Active imaging sensors include radar and laser, while nonimaging sensors are SIGINT, MASINT, and chemical/biological. Passive imaging sensors are compared in Table 61.1.

There are many active imaging sensors (Fig. 61.4) such as SAR, a radar that uses its forward motion to synthesize the equivalent of a large side-looking antenna to produce high-resolution ground mapping. Moving Target Indicator (MTI) is a radar mode that uses differences in Doppler frequency due to the target's motion to distinguish it from stationary backgrounds (i.e., ground clutter). MTI has a wide field of view. Foliage penetration is radar using VHF/UHF frequencies and complex algorithms optimized to detect targets through foliage (VHF: very high frequency; UHF: ultra high frequency). Trees and leaves cover a good portion of the world's terrain. Inverse SAR is a radar mode using a target's angular movement (instead of using the platforms as for SAR) to detect moving objects, and Interferometric SAR is a radar technique using widely separated receivers to receive the same signal and combining them to produce three-dimensional (3-D) maps with highly accurate terrain relief. High resolution radar is radar using short wavelengths (millimeter wave) and sophisticated algorithms to produce high resolution (i.e., measured in inches) imagery. Laser imaging radar is a radar using light (laser), rather than radio frequency (RF) energy, for its illumination source. Robot researchers recognize LIDAR to refer to the acronym *Light Detection and Ranging*, and typically used in

Table 61.1 Passive imaging sensors

Sensor	Advantages	Disadvantages
Film	Best resolution Easily archived	Processing time compromises availability Dissemination copies degrade with reproduction
Electro-optical (visible)	Easy to data link while in-flight High resolution Easy to interpret (literal presentation) High fidelity reproduction	Cannot penetrate inclement weather Volume of data produced (current big data problem)
Infrared (cooled)	Provides imagery during the dark Penetrates some weather or obscurants Detects targets otherwise invisible due to range or background Provides evidence of recently past activity (IR traces), current activity level (engines running), or status (fuel tank levels)	Effectiveness diminished in warmer seasons, desert locales, hotter hours of the day, in Sun's direction Resolution typically 1 NIIRs poorer than that of visible
Infrared (uncooled)	Same operational advantages of cooled IR sensors, but: More compact packaging Reduced power requirements Increased reliability Lower costs	Less sensitive to thermal differences Larger pixel size = less resolution
Spectral	Provides additional operational information about targets—counter CC&D (camouflage, concealment, and deception) techniques	Bandwidth intensive for data relay

Table 61.2 Active imaging sensors

Sensor	Advantages	Disadvantages
Synthetic aperture radar (SAR)	Sees at greater distances than visible Sees through (most) weather and night Provides constant perspective imagery	Power and processing intensive Large aperture
Moving target indicator (MTI)	Detects and tracks moving air/ground objects Builds history of traffic flow over set intervals	A SAR-dependent technique requires further processing of SAR returns
Foliage penetration (FOPEN)	Defeats most uses of foliage as camouflage Provides limited ground penetration capability	Resolution limited due to frequencies used
Inverse SAR (ISAR)	Detects small objects on moving backgrounds Examples: boats, periscopes, and icebergs	Performance varies with aspect angle
Interferometric SAR (IFSAR)	Achieves locational accuracies of 5–30 m Maps large amounts of terrain in a short time	Requires relative positions of receivers be known and maintained precisely Requires extensive post-processing of data
High resolution radar (HRR)	Range limited by frequencies used	Susceptible to intervening weather
Laser imaging radar (LIDAR)	Useful for bathymetry, pollution monitoring, and altimetry Potential for 2-D range-gated and 3-D imaging	Limited in range and by intervening weather

robot navigation. Active imaging sensors are compared in Table 61.2.

Examples of Nonimaging sensors are SIGINT, MASINT, and chemical/biological. SIGINT stands for Signals Intelligence. Electronic signals are passive and the emissions of electronic systems (from radars, navigational aids, and others) can be intercepted and interpreted. The challenge with SIGNIT is frequency hopping and spread spectrum. Another facet of SIGNIT is the interception of spoken communications signals (through radios, etc.). The common challenges with communication signals are digitization, encoding, enciphering, and/or frequency hopping. Measurement and Signatures Intelligence (MASINT) can be either ac-

tive or passive. MASINT adds additional dimensions to target data, but requires the intelligent interpretation of this data. Finally, chemical/biological agent sensors can also be passive or active. There are two types of chemical/biological (Chem/bio) sensors: point and remote, and these types of sensors perform based on air sampling and can detect when previous chemical or biological weapons have been used. Thus, Robots have many options for payloads, dominated by weight, power consumption, and field of view. EO/IR are the most commonly used sensors for surveillance. Its selection is based on resolution, optical efficiency, and detector responsiveness. Its resolution is a function of its detector array size and the field-of-view of the lens

used. Figure 61.5 is used to determine the desired resolution. Optical efficiency is dependent on lens diameter, lens focal length, and pitch. Finally, detector responsiveness is based on the detector's material, wavelength, and temperature. These are all physical parameters. A figure of merit used for a better payload is the product of its normalized resolution with a normalized optical efficiency with normalized detector responsiveness coefficient.

In summary, both **EO** and **SAR** sensors are approaching their limits of *immutable laws of physics*. The challenge today is in data reduction and its exploitation in support of surveillance. As a rule of thumb, surveillance sensors are selected based on:

- **VHF/UHF SAR** is used for foliage penetration and large area coverage.
- Microwave **SAR** for high resolution imaging from standoff ranges.
- Microwave ground moving target indicator (**GMTI**) radars for detecting moving targets and large area coverage.
- Electric support measures (**ESM**), **SIGINT**, and communications intelligence (**COMINT**) for intercepting, locating, recording, and analyzing radiated electromagnetic signals.
- Film for high resolution target classification/identification.
- **EO/IR** for targeting and target classification/identification.

A similar security payload also incorporates **EO/IR** sensors, but with resolution that commensurate with its shorter range to targets. As a rule of thumb, security sensors are selected as:

- Radar is used to detect moving targets at a long range.
- Radar for close-in target tracking.
- **EO/IR** for close-in target tracking.

Surveillance data is either stored for later use, or transmitted to exploitation centers for processing. Security data can be processed onboard the robot or transmitted to the operator control console for real-time observance or for limited post-processing. The key for security is in its algorithms with respect to detecting, identifying, and tracking a potential target or suspicious activities. If weight and processing power is not an issue, multiple overlapping sensors are used on robots to reduce false detections and confirm target identification [61.12]. This is a layered approach. Performance is increased when a wide area surveillance system is used for initial detection or cross-cueing. For example, an

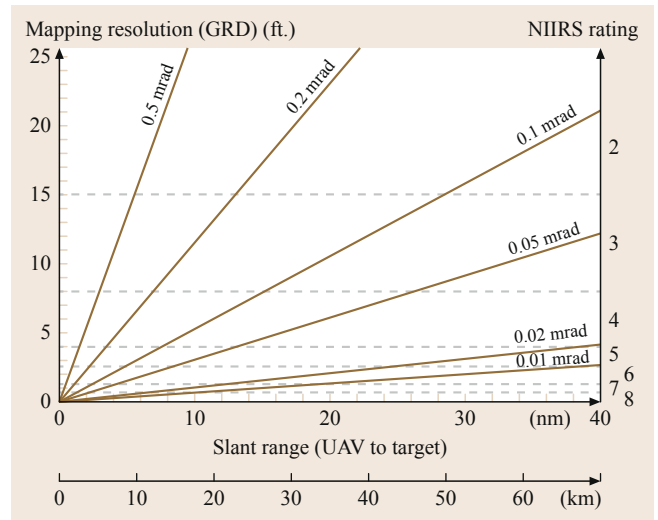


Fig. 61.5 Determining sensor resolution for **ATR** or **RSTA** (courtesy of L. Newcome)

MTI sensor can provide a wide area search and collect coarse information about potential targets sufficient to cue the narrow field of view **EO** and **IR** sensors that can continue the process of tracking, classifying, and identifying potential targets. Payload sensors collect data, but it is the processing of the data into information that can be used by others that is the nugget for both the surveillance and security communities.

61.3.3 Detection and Tracking Algorithms

An important technology in surveillance reconnaissance, surveillance, and target acquisition (**RSTA**). This topic is also closely associated with intelligence, surveillance, and reconnaissance (**ISR**) and automatic target recognition (**ATR**). **ATR**, **RSTA**, and **ISR** are age-old problems in the military to identify and classify activities of interest in the environment [61.13–16]. During surveillance, the user has an option to acquire a target at a specified location, search an area or sector for either stationary or moving targets, perform a panoramic reconnaissance of an area or sector, initiate fire control, or manually control its sensors by a human operator to acquire surveillance imagery as depicted in Fig. 61.6. For example, if the sensor is stationary and the target is stationary, than a maximum-average-correlation-height approach where a bank of linear correlation filters are optimized to respond to the presence of a specific target object by producing a peak at its corresponding location can be very effective. If a stationary target search is used, the platform is directed to search a specified area for targets using stationary target detection and recognition algorithms.

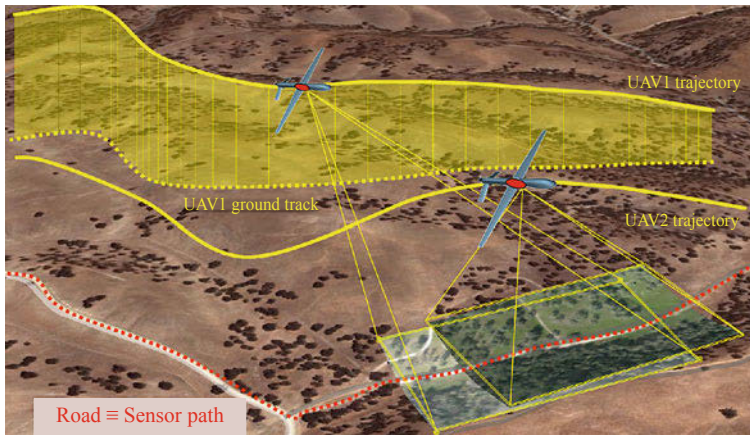


Fig. 61.6 UAV sensor coverage with aircraft trajectory (courtesy of University of Illinois – Urbana Champaign)

These algorithms can detect both stationary and moving targets, but moving target detection does not make use of motion related information that is associated with a robot. Moving objects in the scene are the subjects of interest in most visual surveillance applications using EO/IR sensors. Specifically, the actions of the moving objects need to be monitored and appropriate flags need to be raised when events of interest occur in the scene. The mobile platform needs to be controlled so as to aid the surveillance task. Thus, the objectives of the surveillance task and the associated real-time computation constraints involve difficult challenges in building highly robust yet computationally cheap algorithms for detection, classification, and correspondence.

Manually, the user can select several options including the type of search modes to be used in which the sensor is assumed to be either stationary or moving, and the target is assumed to be either stationary or moving. For example, a UAV and satellite are always in motion, while the UGV/USV/UUV can either be either stationary or mobile. The selection of the stationary target mode causes stationary target detection and recognition algorithms to run, while the selection of the moving target mode causes moving target detection and tracking algorithms to be executed. The user would benefit from an automatic selection feature. The demanding nature of the required detection criteria for surveillance and security necessitates the integration of complementary technologies which can sense motion, characterize patterns, find thermal signatures, and capture temporal behavior as can be seen in [VIDEO 678](#).

The RSTA or ATR algorithm sequence [61.17] include reconnaissance, acquire target through search, and finally target tracking. A panoramic reconnaissance command can direct the robot's payload to collect a mosaic of images over a wide field of regard and send it to the operator for manual viewing. There are several techniques used to create an image mosaic from a se-

quence of images. The registration between images is obtained by minimizing the sum-squared error of image intensities at each pixel. Although this technique produces very accurate registration results, it tends to be slow, and typically require operator interaction to initialize the registration function. The collected mosaic may be used to assess trafficability, check out regions of interest such as roads and bridges, and manually look for enemy targets. To acquire targets, the vehicle is directed to look at a particular map location or in a particular direction, acquire an image, and perform stationary target detection on that image. An operator can select several search options in which the robot is assumed to be either stationary or moving, and the target is assumed to be stationary or moving. The search area determines whether to search a map region or an azimuth-elevation wedge. An azimuth may be specified relative to the world (map) or specified in vehicle coordinates. The selection of the stationary target function causes stationary target detection and recognition algorithms to run, while selection of a moving target mode causes moving target detection and tracking algorithms to be executed. The search mode determines whether to search an area in a single time or multiple times frames. An EO/IR sensor can use a combination of image processing algorithms. Probing-type algorithms include connected-component analysis or a blob analysis.

A large body of image processing algorithms has been developed to detect targets using techniques including histogram manipulation, convolution, morphology, over- and under-sampling, quantization, and spectral processing using Fourier transforms and discrete cosine transforms (DCTs). These algorithms tend to be computationally intensive [61.18, 19]. Other popular ATR algorithms include binary template matching, multispectral imaging, and wavelet transformation techniques. Of the many types of image enhancement algorithms, a spatial convolution kernel filtering tech-

nique produces the most dramatic results. A convolution kernel generates a new pixel value based on the relationship between the value of the pixel of interest, and the values of those that surround it. In convolution, two functions are overlaid and multiplied by one another. One of the functions is the video frame image and the other is a convolution kernel. [ATR](#) algorithms can be broadly described sequentially as: target detection, a segmentation function, feature evaluation, and classification. Target detection approaches can be either image-based or model-based.

If stationary target search is used, the platform is directed to search a specified area for targets using stationary target detection and recognition algorithms. These algorithms can detect targets using blob extraction and blob tracking algorithms. When a potential target is detected, images are sent to a target recognition algorithm for additional processing. Target recognition can be accomplished through the use of a *hashing* algorithm. Various target detections are passed to the hashing algorithm for labeling as one of several target types contained in a database or perception library. The hashing algorithm also produces an estimate of target pose and when the processing is complete, the results are sent to the operator for verification. Moving objects are typically detected using background subtraction. For this type of search, the platform is directed to look at a specified area for targets using a moving target detection algorithm based on temporal differencing. Most surveillance systems use background subtraction as an efficient means of motion detection with a stationary camera. Unfortunately, background subtraction techniques are not always robust under camera jitter, varying lighting conditions, and moving foliage. Techniques such as affine transformations are used for image stabilization. Problems of a periodic nature such as jitter and moving foliage induce multi-modal distribution of pixel intensity values. If the classification of the background environment can be calculated, then the background can be subtracted from the image to enable the use of motion detection and segmentation algorithms.

One popular method for background model generation is the incorporation of autoregressive ([AR](#)) or infinite impulse response ([IIR](#)) filters. A single [AR](#) or [IIR](#) filter is used for each pixel to estimate the dominant mode of the background. The [AR](#) filter estimates the center and width of the dominant mode of the background, and it is associated with each filter per pixel is a value that approximates the probability that the mode represented by the filter is seen by the pixel. When an intensity value is seen by the pixel falls within the mode of one of the pixel's filters and the associated probability is greater than a preset threshold, then

the pixel is declared as background. When a particular intensity value is not represented by any of the filters for that pixel, a new filter is added with an associated low probability value. When a filter matches intensity value, its probability rating is increased and the probabilities of the rest of the filters associated with that pixel are decreased. Thus, at each detection cycle, the filters corresponding to a pixel adapts to better fit the values of its background. This motion detection technique is enhanced by the use of feedback from higher-level algorithms such as a classifier and/or a correspondence algorithm. The classifier has the capability to reject spurious detections. This information can be used either to create a new filter for the pixel or to increase or decrease the probability threshold for detection. Information from its correspondence can be used to predict future locations of detections. This considerably improves the quality of segmentation. Another correlation-based tracker function can be added, which controls the payload pan/tilt gimbal to keep a detected target centered in the image. A harder problem is when the target is moving and the sensor is also moving.

For security robots, camera-based [EO/IR](#) sensors have long been used for security and observation purposes as depicted in [VIDEO 681](#). Surveillance cameras are typically fixed at known positions and have coverage of a circumscribed area defined by the fields-of-view of the cameras. Although some recent vision research has addressed autonomous surveillance, in most cases, humans perform the sensory processing. For an autonomous surveillance example, a vision system can provide the geometric shape of the target and its angular location relative to a radar sensor, while its onboard radar system can measure both the distance to the target and its relative velocity radial to the vehicle. The target's perceived geometric shape and distance are then used to calculate its cross-section for purposes of human target classification. The complementary mix of using multiple sensor (camera and radar) technologies allows for greater than 99% probability of detection with less than 1% nuisance alarm rate (also known as false-positives) for fielding a robust security system. This is a good example of cross-cueing. Camera control can be seen in [VIDEO 702](#). Once a target is detected, it is tracked in the center of the collective field-of-view in order to provide verification using successive vision and radar-based detections. A track file is maintained on each detected target to correlate size, distance, speed, and other parameters over an extended period of time. This time-based integration approach allows the system to significantly reject nuisance alarms while using extremely high gains during the detection process. The classification procedure in a security application maps

a given image sequence of a moving object to the most likely class label by classifying each image independently and then classifying the resulting set of class labels. The classifier can also reject classifying an object. For example, a classifier on the mobile detection assessment and response system (MDARS) program has demonstrated class-conditional sequence error rates of less than 5% and a false alarm rejection rate of 80% in disjoint testing. Unknown objects and novel views of known objects are detected by considering the class label history over an image sequence. Image sequences that yield a significant fraction of rejections or cause atypical classifier confusion are saved for later human interpretation.

In the last step, the temporal correspondence of a moving object plays a very important role in classifying, tracking, and interpreting an object's actions. Large number of targets of varying sizes in a scene preclude the use of simple positional correspondence, i. e., correspondence based purely on the positions of moving objects. In such situations, other features of the moving objects, such as different appearance traits, need to be considered for robust correspondence. For example, the measure of goodness of the features can be chosen not only on the object in question, but also on other objects in the scene. A globally *good* set of features can be estimated a priori, but only a subset of these features might be relevant to the correspondence of a particular object. Carnegie Mellon University (CMU) has developed a technique called *differential discriminative diagnosis* in which it provides a systematic method for estimating the relevance of features and checking the temporal consistency of these features for a particular object. The correspondence task is performed with a two-part process. The first part relies on positional correspondence using linear prediction. This part nominates a set of likely candidate matches for a reference object. The second part uses appearance-based correspondence to find the best match among those nominated by linear predictions. A simple linear classifier is trained based on learning techniques to determine whether or not two images are of the same object. Differential discriminative diagnosis identifies those features that are most relevant to the correspondence problem. Efficient correspondence is achieved by enforcing the temporal consistency of the *relevances* determined for a particular object, and this technique has demonstrated correspondence among moving objects with an accuracy of 96%. Target correspondence across multiple sensors can be achieved using a maximum a posteriori (MAP) estimate of the observation sequence to maximize target appearance and spatiotemporal probabilities. A correspondence problem is also used in stereo vision.

Another approach is to perform the correspondence step using a multiple robots configuration as in a swarm, which is addressed further in the multiple vehicle *ATR* active research area to follow (in Sect. 61.4.4). A more complex scenario involves multiple sensors detecting several targets simultaneously, and a moving sensor payload detecting a moving target [61.20, 21]. A moving target causes the radar signature to shift outside the normal return of a radar image. This shift in frequency (a Doppler shift) is used to distinguish stationary targets from moving targets. The detection of a moving target is more difficult when the sensor is also in motion. Augmenting data such as speed and heading of the moving target can be used to better *profile* potential targets. Other factors such as size, radar cross-section, and environmental clutter are used to make assumptions governing the type and intent of the target. *MTI* cross-cueing data has been overlaid in real-time on to 3-D visualization of the terrain to allow an operator to quickly locate a target such that the *EO/IR* sensor could be rapidly slewed to the target of interest. Test results have shown that wide field-of-view *MTI* radar that is used to cue a limited narrow field of view *EO/IR* sensor has drastically increased situational awareness on the battlefield. The next evolution is to automate the cross-cueing process in order to track, classify, and identify potential stationary and moving targets [61.22].

61.3.4 Human–Machine Interface

Unmanned aerial robots that are used for surveillance come in all types from the smaller, hand launched Raven, Puma, and Wasp drones to the mid-size Aerosonde and ScanEagle to the larger Predator, Reaper, and Global Hawk platforms that can stay airborne for 24 to greater than 28 h missions [61.23]. The Global Hawk architecture is depicted in Fig. 61.7 with its many communication links. The larger *UAVs* and their ground segment components interact through an over-the-horizon (*OTH*) satellite relay and line-of-sight (*LOS*) links to maintain command and control and sensor data dissemination communication paths for launch, flight, and recovery. Bandwidth compression is applied to the sensor data to maximize area coverage and data throughput. The communications systems are being designed to minimize susceptibility to jamming and interception. Dissemination of *UAV* collected intelligence is made through direct downlinks to national and theater intelligence centers and other exploitation systems, or through established *hard* communications between *UAV* ground control stations, and the exploitation systems. The *UAV* ground control station has limited capabilities to disseminate collected intelligence directly to an exploitation ground system

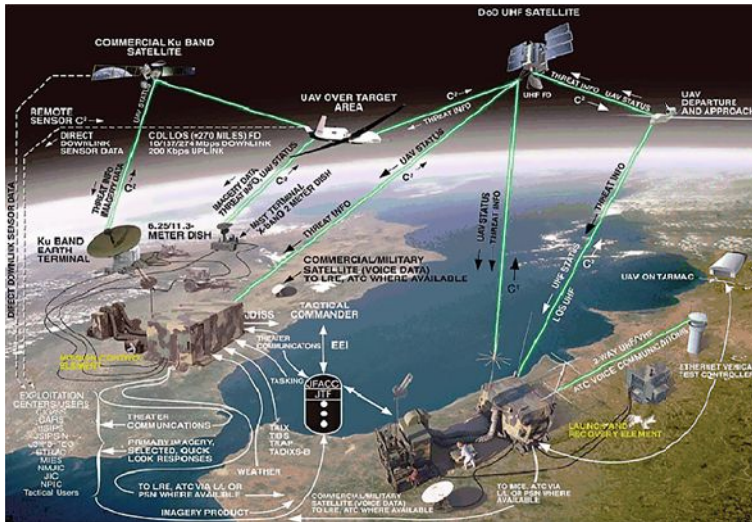


Fig. 61.7 Global Hawk UAV architecture (courtesy of Northrop Grumman and Raytheon)



Fig. 61.8a–c Global Hawk ground elements: (a) ground station, (b) operator seats, and (c) UAV display (courtesy of Northrop Grumman and Raytheon)

or battlefield customer. When deployed, a fully operational system consists of four Predators (with EO/IR sensors), a ground control station (GCS) that houses the pilots and sensor operators for human-machine interface (HMI), and a primary satellite-link communication suite.

The Predator UAV can run autonomously, executing simple missions such as reconnaissance on a software program, or it can run under the control of its crew (Fig. 61.8). The crew of a single Predator consists of one pilot and two sensor operators. The pilot drives the aircraft using a standard flight stick and associated controls that transmit commands over a C-Band line-of-sight data link. When operations are beyond the range of the C-Band link, a Ku-Band satellite link is used to relay commands and responses between a satellite and the aircraft. Onboard, the aircraft receives orders via an L-3 Communication satellite data link system. The pilots and crews use the images and radar received from the aircraft to make decisions about controlling the aircraft. The pilot's main mission is to fly the plane, while the sensor operator controls the cameras that bring the

battlefield into full view to gain intelligence. Unlike other manned missions, pilots for large UAVs only control the plane during landing and takeoff. However, sensor operators do much more than watch the feedback from their cameras [61.24]. Working together with pilots, they do preflight checks, coordinate with the air control tower, and provide feedback to pilots. The intelligence data is streamed back to exploitation elements where the data is analyzed by people on the ground or with automatic detection algorithms. Not including the exploitation element, it currently takes approximately 82 personnel to operate four of the larger UAVs for a 24 h period including technicians and support personnel.

Typically, unmanned ground robots used for security [61.25, 26] are available in limited options from the commercial Vigilus system, Reborg-Q security robot, OFRO (by Quadretex Ltd.) and patrolbot, to the army's mobile detection assessment and response system (MDARS) and its family of integrated rapid response equipment (FIRRE). The MDARS [61.27] system consists of ground robotic platforms capable of

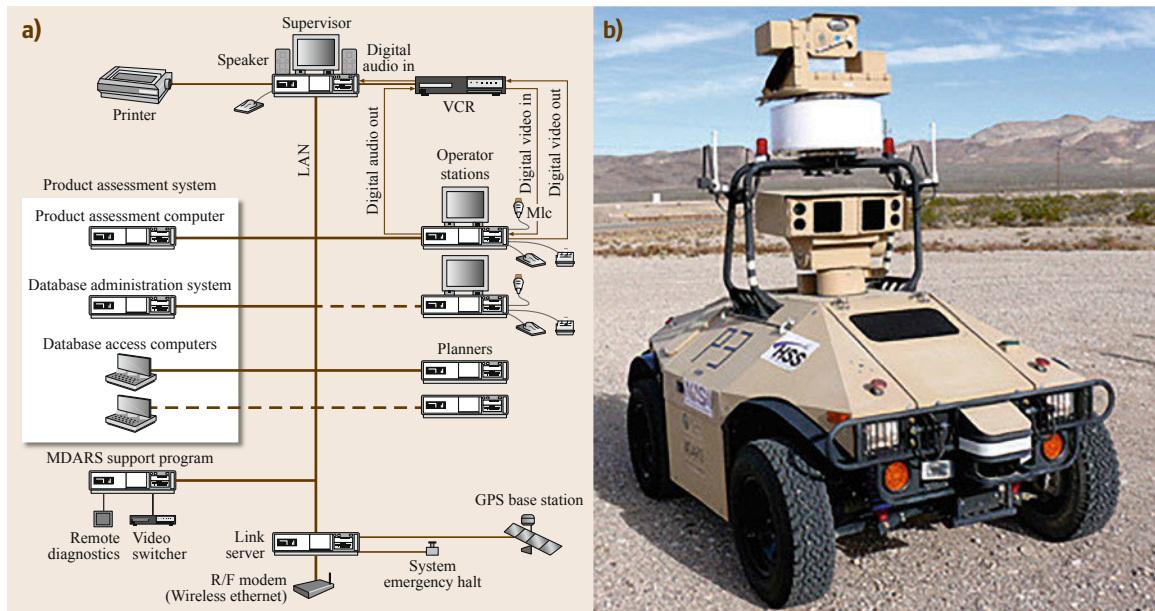


Fig. 61.9 MDARS operational concept and system components (courtesy of Space and Naval Warfare Systems Center (SPAWAR), Pacific)

preprogrammed autonomous movement, motion detection, an incident assessment subsystem, and two way communications capability between operator and robot. Its operational configuration will consist of pair(s) of mobile platforms employing a suite of sensors that are preprogrammed or remotely controlled by an operator located at a remote monitoring and control station. The actual number of fixed and mobile patrol units for a given location will be site specific. The MDARS Increment 1 system components are depicted in Fig. 61.9 with its various interfaces. All such robots and sensors (known collectively as resources) are controlled by the multiple resource host architecture (MRHA), with minimal human (i. e., security personnel and operators) supervision required [61.28]. The individual processors are connected via an Ethernet local area network (LAN) that supports a peer-to-peer communications protocol (expandable to 32 platforms or robots). The user interface provides a *big picture* representation of secured areas and system resources. User intervention is required only when a platform encounters an exceptional condition such as an environmental hazard or a security breach.

The operator control unit is either in monitor mode, in which the operator observes and monitors the status of the robot and sensors, or the operator is in direct control of a single resource such as a single robot in a multi-robot system. Moreover, the robot itself carries a number of sensory systems, each of which must also be controlled individually. For example, MDARS may

have eight cameras, two radars, and four lights, but only a single camera, radar, and light is controllable at any given time as shown in [VIDEO 680](#). Multiple cameras can be viewed simultaneously, but the operator cannot pan two of them at the same time. A joystick button or dialog button can be configured to cycle between the various payloads. The control of the resources and each of its selected subresources is integrated in such a way that a single joystick can be used to perform all relevant joystick tasks. As an example, the operator can pan the selected camera with the joystick, and then press a button to put the robot in teleoperation mode and drive the robot using the same joystick. The concept of modes is used to provide rich control features for each resource. This paradigm reduces the complexity of the software and simplifies the user interface presented on its displays, while still giving the operator full control of each asset. The MDARS control station allows the operator to execute preplanned patrols, random patrols, or user-directed patrols as seen in [VIDEO 701](#). Automation of sensor selection would improve operations.

The controller displays can perform basic image processing, which means they take in video at a certain resolution, and display it in the display's native resolution [61.29]. Video processing is the act of scaling, which is converting an incoming video signal from one size or resolution to another in order to work with the display panel. This is what is usually referred to as *video processing*, and it is a minor feat compared to video enhancement. Video enhancement techniques can

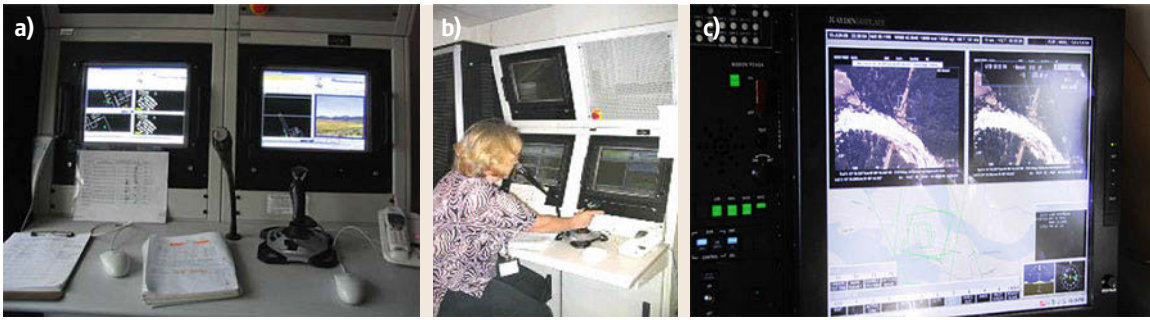


Fig. 61.10a–c MDARS mission control center. (a) Control station, (b) MDARS operator, and (c) display (courtesy of SPAWAR)

be based on spatial domain methods or frequency domain methods [61.30]. Image enhancement algorithms offer a wide variety of approaches for modifying images to achieve visually acceptable images. The choice of techniques implemented is a function of the specific task, image content, observer characteristics, and viewing conditions. Mosaic images provide better visualization of a tracking scenario. All security sensors are fused together to form a composite *threat score* on potential targets, and intruder alarms are reported to the user on the MDARS console (Fig. 61.10). Also, the intruder's range and bearing are displayed on a map

window and a digital stream from the camera is shown in a video window. For ATR, the operator receives notification of a target by the appearance of an icon on the map display at the operator interface. Selecting an icon brings up a target verification panel and a target response panel showing the imagery associated with the target that was provided by the sensors. With experience, most operators became comfortable and competent with normal operations, and each acquiring variable levels of proficiency in responding to exceptional events such as dealing with intruders or taking manual control of the robot.

61.4 Active Research

In addition to enabling robotic surveillance and security technologies, there are many active areas of robot research, such as being able to produce high-quality imagery from a mobile platform that poses a number of challenges. In addition to issues related to camera motion and the resulting image perspectives, the quality of the video imagery can also be compromised by poor environmental conditions, data link degradations,

and bandwidth limitations. Atmospheric factors such as poor lighting at dawn, dusk, or night time, the presence of shadows, target occlusion and adverse weather, including sandstorms and variable clouds, can obscure important details. Some identified areas of interest include: Sect. 61.4.1 in solving the data processing problem due to the large amounts of sensory information collected, Sect. 61.4.2 detecting human activity in

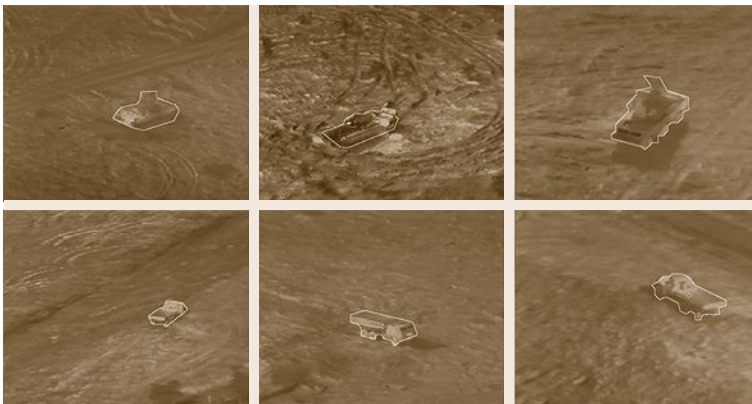


Fig. 61.11 Automatic target recognition (courtesy of Bilkent University)

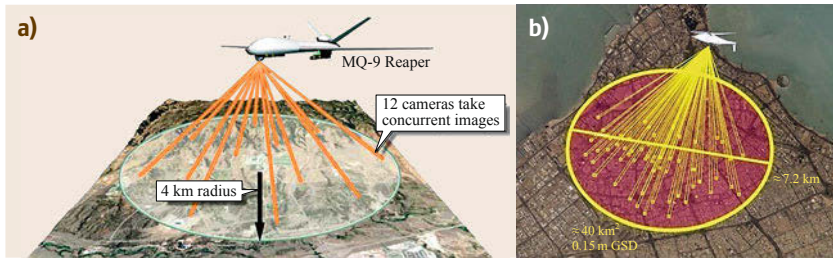


Fig. 61.12a,b Multiple real-time video stream sensors. (a) Gorgon Stare (courtesy of Sierra Nevada Corp) and (b) ARGUS-IS (courtesy of BAE Systems)

support of surveillance, Sect. 61.4.3 facial recognition for security identification purposes, and Sect. 61.4.4 collaborative **ATR** by multiple robot in either heterogeneous or homogeneous systems.

61.4.1 Solving the Data Processing Problem

With all the useful information that **UAV**s provide comes the problem of how to sort through it all and find actionable data. This is the *Big Data* problem for the military. One manual solution to the data explosion problem is to tag the data, store it, and retrieve it when needed. Unfortunately, this information would not be timely. Data fusion involves the use of techniques and software that combine data from multiple sources and analyze the data to make it useful for the end user [61.31]. Data fusion can involve the combining of data (such as **UAV** video) with a **GIS**, which adds location and time data to the images gathered (Fig. 61.11). To accomplish this, the raw data has to be combined with metadata, which is information about the data that enables the data to be combined. On-going research such as with *intelligent search* is another tool that can be used to make **UAV** data more accessible. Based on modern artificial intelligence (**AI**) techniques such as machine learning, depth first searches using iterative deepening, or depth first searches based on space complexity, users can quickly personalize a search to make relevant data more easily available [61.32].

To help users retrieve information, one promising method, called natural language processing, discovers user preferences and needs by either extracting knowledge from what users are looking for or by interactively generating explanatory requests to focus users on the information they are interested in [61.33]. The use of natural language to improve the performance of the intelligent search engines is one aspect of **AI**. Other related **AI** technologies for automated processing include object recognition and statistical machine learning, or application of **AI** in intelligent search is facial recognition. One promising solution that could help with the data overload issue is more efficient techniques for sensor fusion. For example, a multisensor fusion algorithm that can bring together

information from multiple platforms about a particular target of interest in a unified display would be beneficial to the operator. Researchers will need to develop smart technologies that automate the entire process of archiving, tagging, retrieving, managing, and displaying data and other information gathered by increasingly sophisticated sensors. As an adjacent topical area, machine-to-machine interfaces will need to become much more transparent in order to handle the data deluge [61.34].

A future technology called wide area surveillance (Fig. 61.12) is based on a new sensor system called Gorgon Stare, a video capture technology that uses a spherical array of nine to twelve cameras attached to an **UAV**. With so many sensors, Gorgon Stare needs to utilize a system of tagging and incorporating metadata to be fully effective. Initial reports on the progress of Gorgon Stare is that there are deficiencies in its **IR** performance, having *numerous* interoperability problems, having a lack of stability of the sensors, and encountering reliability problems. These issues can be overcome as the program matures. Unfortunately, the new sensor system is still limited by the human's inability to process the information gathered from many cameras, or rely on advanced automatic processing techniques to fuse the information into the coherent picture.

61.4.2 Detecting Human Activity in Support of Surveillance

The problem of using computer vision to track and understand the behavior of human beings is a very important tool for surveillance and security operations. At its highest level, this problem tries to recognize human behavior and understanding intent and motive from visual observations [61.35, 36], and [61.37]. This is a difficult task, even for humans to perform, and misinterpretations are common. The problem has several subareas of human motion recognition, surveillance, tracking, and activity detection. In the area of surveillance, automated systems to observe pedestrian traffic areas and detect dangerous action are becoming important. Many such areas currently have stationary surveillance cameras in place. However, all of the image understanding



Fig. 61.13 Monitoring individual and group human activities (courtesy of University of Minnesota)

and risk detection is left to human security personnel. This type of observation task is not well suited to humans, as it requires careful concentration over long periods of time. Therefore, there is clear motivation to develop automated, intelligent, vision-based monitoring systems that can aid a human user in the process of risk detection and analysis. Eventually, this capability will migrate from stationary cameras to mobile security applications.

Most of these human activity applications require an automated recognition of high-level activities, composed of multiple simple (or atomic) actions of persons as depicted in Fig 61.13. The goal of human activity recognition is to automatically analyze on-going activities from EO/IR sensors through a sequence of image frames [61.38]. There are various types of human activities and depending on their complexity, human activities can be categorized into four different levels based on: gestures, actions, interactions, and group activities. Gestures are elementary movements of a person's body part and actions, and is defined as single-person activities that may be composed of multiple gestures organized temporally. Interactions are human activities that involve two or more persons and/or objects as shown on VIDEO 683, while group activities are the activities performed by conceptual groups composed of multiple persons and/or objects. Promising events for activity monitoring include the detection of loitering individuals [61.39], and the detection of unusual crowd activities [61.40], which can be difficult to discern from normal crowd activities. It would be useful for security robots to detect motion in restricted areas [61.41], detect perimeter breaches, and detect when security cameras are tampered with [61.42]. Also of interest which may or may not involve the human include the throwing of an object or the detection of an abandoned object. The University of Minnesota has done

work in detecting abandoned objects as referred to in VIDEO 682.

There are several approaches used in the recognition of different levels of activities. Single-layered approaches are approaches that represent and recognize human activities directly based on sequences of images while hierarchical approaches represent high-level human activities by describing them in terms of other simpler activities. Single-layered approaches are divided into two classifications depending on how human activities are modeled directly from the video data: space-time approaches (a sequence of two-dimensional (2-D) images placed in chronological order) and sequential approaches (a sequence of observations). Unfortunately, the majority of activity monitoring algorithms is far from being real-time, which is an issue for surveillance. Robot surveillance is demanded in today's environment where the tracking and monitoring of people is an integral part of everyday activities. Monitoring is typically accomplished with multiple cameras [61.43] and from multiple vantage points. Activities of interest vary widely from throwing an object [61.44] to the subtle task of abandoning an object such as a backpack or leaving on unknown package [61.45]. In many instances, it would be important to estimate or count the size of a gathering [61.46–48]. Activity monitoring suffers from the same issues associated with ATR such as signed noise, tracking issues, and segmentation issues arising out of the stabilization of video images. There are a large number of new and promising improvement methods on the horizon, including space-time feature-based approaches, manifold learning, rigid/nonrigid motion analysis, and hierarchical approaches.

61.4.3 Facial Recognition for Security Identification

In order for a security robot to perform its mission to protect and safeguard, sometimes it will encounter people which have to be discerned as either friend or foe. In order to make such a determination, face recognition is critical [61.49]. Most of the current face recognition algorithms can be categorized into two groups: image template-based or geometry feature-based [61.50, 51]. The template-based methods computes the correlation between a face and one or more model templates to estimate the face's identity. For the other approach, the geometry feature-based methods analyze explicit local facial features, and their geometric relationships. Face recognition is a two-step procedure consisting of first detecting a face and followed by recognition. Top researchers have argued that the accurate detection of human faces in arbitrary scenes is the most impor-



Fig. 61.14 Local binary patterns using OpenCV (courtesy of Yale University)

tant process involved, followed by the face recognition process. When faces could be located exactly in any scene, the recognition step makes the final determination of classifying the person as being either friend or foe.

Algorithms are used to know how to differentiate between a basic face and the rest of the background. If the background is controlled (referred to as being highly structured and uncluttered), an algorithm to remove the background will produce face boundaries. Faces can be found by either using color, motion, or a mixture of both types of information. The detailed steps include acquisition, normalization, and recognition of moving faces in dynamic scenes. Color as a cue can be used for detection and tracking, and provides a computationally efficient yet effective method which is robust under rotations in depth and during partial occlusions. This method can be combined with both motion- and appearance-based face detection. The main idea is to model a class-conditional density for each person in a representation space of relatively low dimensionality. Unfortunately, color detection doesn't work on all kinds of skin color, and is still susceptible to varying lighting conditions.

Humans must periodically blink to keep their eyes moist, and detecting a blinking pattern in an image sequence is a reliable means of detecting the presence of a face. Blinking provides a space-time signal which is easily detected and unique to faces. Detection by blinking is precise, but requires capturing an image pair during a blink. A common technique for recognition is the correlation with a set of Eigen images. Better results have been demonstrated by combining stereo, color, and face detection techniques into an integrated approach [61.52]. Depth estimation using stereo cameras is used to eliminate background effects. Skin-hue classification identifies and tracks likely body parts within the silhouette of a user, while face pattern detection dis-

criminates and localizes the face within the identified body parts. Other approaches to finding faces include the use of neural networks, taking advantage of statistical cluster information, and model-based face tracking. Related work continues using edge-based methods and geometric models such as edge-orientation matching and using the Hausdorff distance measurement. The leading face finding algorithm in unstructured environments is based on a series of weak classifiers such as Haar-like features, representation by integral images, and a method for combining successively more complex classifiers in a cascading structure which can increase the speed of detection by focusing attention on promising regions of the image. An example of facial recognition can be seen in [VIDEO 553](#).

Upon detecting faces, facial recognition has numerous distinguishable landmarks, where different peaks and valleys make up facial features (Fig. 61.14). Measurements of these features include:

- Distance between the eyes
- Width of the nose
- Depth of the eye sockets
- The shape of the cheekbones
- The length of the jaw line.

The 2-D (or 3-D) image of the face is compared to a database of known people's faces. After detection, the image is analyzed to determine the head's position, size, and pose estimation. The sensor measures the curves of the face to a submillimeter scale to create a template. This face template is translated into a unique code that represents the features on the face. This is followed by a matching function that compares the image taken with a database of known faces. This is followed by a verification step that identifies the person in the image.

Skin biometrics can be used to verify the match. Techniques such as Surface Texture Analysis, Local Feature Analysis, and Vector Templating are used to improve the match. There are some impediments to facial recognition such as a lack of resolution in the sensor, glare from glasses, obscuration due to long hair hiding features of the face, and poor lighting conditions. The wider issue is to obtain and maintain an up-to-date database for matching. It would be simple to keep records on who belong to the facility, and to declare unknown faces as foes. However, there will be instances that the human is not a foe, but does not exist in the database either. Another issue would be a scenario in which there are multiple human intruders that stretches the capability of the robot security system. As a final verifier, the human operator can be used to make the final determination as friend or foe, visually or through an interrogation process.



Fig. 61.15 Collaborative ATR (courtesy of NATO)

61.4.4 Collaborative ATR

Swarm robots are a new approach to the coordination of multi-robot systems that consist of large numbers of robots, either homogeneous or possibly heterogeneous robots, i. e., team of air and ground platforms as depicted in  VIDEO 700. Swarming implies that a collective behavior emerges from the interactions between robots or the interactions of robots with its environment [61.53, 54], and [61.55]. In a coordinated team approach, individual platforms are able to pass target location information to one another during a target search operation in an attempt to get confirmation of a suspected target. Thus, a robot that detects a target passes the target's location (and a surrounding map-based uncertainty region) to another robot for confirmation. The confirming robot searches the nonoccluded portion of the given map region for the detected vehicle and returns the results of its search to the originating vehicle where they are compared with the original search results (Fig. 61.15). A final target's result is compiled and sent to the operator for verification.

The intent of cooperative target search is to increase the accuracy and reliability of the target search process. The conditions under which this search is guaranteed to be accurate must deal with the following issues:

- It is unclear under what conditions the originating vehicle can be sure that a positive response from the confirming vehicle corresponds to the same target or to any target at all.
- If the orientations of either or both robots are off significantly from their true orientations, it may be that the vehicles are not searching the same map region or that different targets within the uncertainty region are reported as the same target.
- Cooperative target searches puts stringent demands on the accuracy of vehicle orientation estimates. This problem can be partially alleviated by having

reliable, long-range laser rangefinders on all participating robots.

- Cooperative target search also puts stringent demands on the accuracy of target detection and recognition algorithms. For example, it is not unusual for an unsophisticated target detection algorithm to generate a positive return from a warm rock or large animal.
- The fact that the confirming vehicle may return a positive response does not increase the probability that the object is actually a valid target. In trials, confirmation of nontargets has actually been observed in field testing.
- It is also difficult to tell whether the confirmation of a valid target results from observation of the same target or detection of a false target. To alleviate this kind of problem, accurate and sophisticated target recognition algorithms are required.

Another concern is when the confirming robot returns a negative response. This lack of confirmation may indicate nothing more than that the confirming robot is looking in the wrong area or that it simply failed to detect a target that is present in its sensor's field-of-view. At this point, it is unclear under what conditions the originating vehicle should disregard its own initial detection. These issues provide motivation for researchers to develop more sophisticated ATR algorithms to obtain higher confidence reports and reduce the number of false alarms. These same issues also provide motivation for the development of context understanding algorithms.

Since cooperative target searches place these stringent demands on the accuracy of vehicle orientation estimates, teams of surveillance platforms must solve the multi-robot distributed estimation problem [61.56] and the related source localization problems [61.57]. Each of the robots collects sensor data regarding its own motion and shares this information with the rest of the team during periodic update cycles. A single estimator, possibly in the form of a Kalman filter, processes the available positioning information from all the members of the team and produces a pose estimate for every one of the robots. The equations for this centralized estimator can be written in a decentralized form, therefore allowing this single Kalman filter to be decomposed into a number of smaller communicating filters. Each of these filters processes sensor data collected by its host robot. The exchange of information between the individual filters is necessary only when two robots detect each other and measure their relative pose. The resulting decentralized estimation schema, which referred to as *collective localization*, constitutes a unique means for fusing mea-

surements collected from a variety of sensors with minimal communication and processing requirements. What complicates the estimation is that the robots are moving and the targets (or multiple targets) may also be moving.

Researchers have introduced a simple updating rule defining a distributed estimation scheme that balances consensus with tracking. It was shown that the probability distribution of the vector of estimates obeys a *Master Equation* derived from first and second moment dynamics. From this master equation, the evolution of its mean estimate and its variance can be computed. If the individual robots ignore the discrete state and simply do consensus, the estimates converge with the probability of *one* to the average of the initial values of the estimates. Moreover, by appropriately weighting the discrete state in the update rule, the average can be tracked with an arbitrarily small variance at steady state conditions.

Source localization is addressed by incorporating a visual gradient-based approach for a robot to adaptively search a location-unknown source. While mov-

ing, the robot only measures the received image quality and adaptively decides the motion direction in each time instant. Simulation results indicate that the robot can reach the sensor when the initial signal-to-noise ratio (SNR) is as low as 0 dB and the standard deviation of motion errors is 10% of the motion step size. Due to the adaptive nature of this solution, this approach is robust to measurement noise and motion errors. Since the robot moves along the direction of the gradient estimated at each time, the approach can be applied to an arbitrary signal strength distribution in an area [61.58]. One of the scenarios can be in an environment of obstacles so that the robot at the initial location does not have a line of sight to the sensor. The other scenario to consider is that the source is a cluster of activated sensors that send signals at the same time. Thus, the gradient approach can be extended from 2-D to 3-D space for applications incorporating aerial vehicles [61.59]. A multi-robot system can be applied to both the surveillance problem and the security scenario, but continued research is required to make such a system robust and practical.

61.5 Conclusion

Robots for surveillance typically involve unmanned aerial vehicles that can cover large areas and sit on regions of interest to provide a persistent presence [61.60]. UAVs today utilize teleoperation or flies via way-points on longer traverses to search selected regions. During flight, there are instances in the mission profile where launch and recovery operations are also autonomous. With EO/IR and SAR payloads, the data is streamed back to processing elements for post-processing. This becomes a bottleneck due to the high number of platforms in theater and the enormous volume of data that cannot be processed in real-time. These operations are also highly susceptible to weather issues, and impacted by delays and bandwidth limitation issues associated with the many communication links utilized. Collaborative ATR with swarms of vehicles is an emerging capability, but introduces its own set of issues in terms of consistently and correctly identifying targets of interest. Finally, there are related efforts in ground and unmanned surface water (USV) RSTA, and present different environmental-type challenges such as handling sensor motion issues due to buoyancy or flying indoors (see VIDEO 703).

Security robots are a maturing capability, but yet to be commonplace. The vision is to have a single operator commanding multiple stationary and mobile robots to deter criminal activities, especially the destructive

actions of some people. The overall mission is to detect, assess, and take action in order to deter a potential threat. Typical robots include ground platforms, hovering type vehicles, and surface water vehicles of all sizes. Key issues include the monitoring of human activities, detecting faces, and determining the extent of the potential threat. With multiple sensors available to



Fig. 61.16 Humanoid KUBO as a security guard (courtesy of Korea Advanced Institute of Science and Technology (KAIST))

the operators, there will be limited opportunities to confirm the target or set of targets due to time sensitivities. Moreover, sensor fusion can deliver a more complete picture of the situation for human or automatic confirmation. Affectivity of the system is quantifiable based on measuring coverage, having a high recognition rate, and demonstrating a low false alarm rate. A future direction is to potentially arm the security robots, but this introduces a new series of issues such as liability and ethics. Chapter 80 (Roboethics: Social and Ethical Implications) expands on these larger societal issues.

A future of humanoids (Fig. 61.16) and social robots used for surveillance and security is an inevitable possibility [61.61]. Humanoids (Chap. 67) provide bipedal mobility as a ground robot, and have an inherent

sensor payload with its head. However, the head sensors must be used to both navigate and perform reconnaissance. Its surveillance capability is limited by the field of view and resolution of its head cameras, but has expanded orientation capabilities based on its anthropomorphic neck and torso gimbals. This type of robot can take advantage of existing RSTA algorithms such as human activity monitoring, face recognition, and collaborative ATR for target confirmation as discussed previously. However, all these features are dependent on having adequate onboard processing capability in order to make real-time confirmation and decisions. Who is to say a future humanoid security robot cannot pick up a remote sensor suite similar to binoculars in order to search and detect a potential intruder?

Video-References

-  VIDEO 553 Security: Facial recognition
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/553>
-  VIDEO 554 Surveillance by a drone
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/554>
-  VIDEO 677 Ground security robot
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/677>
-  VIDEO 678 People detection from a UAV
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/678>
-  VIDEO 679 UGV demo II: Outdoor surveillance robot
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/679>
-  VIDEO 680 MDARS I: Indoor security robot
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/680>
-  VIDEO 681 Scout robot for outdoor surveillance
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/681>
-  VIDEO 682 Detection of abandoned objects
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/682>
-  VIDEO 683 Tracking people for security
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/683>
-  VIDEO 700 Collaborative robots
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/700>
-  VIDEO 701 Multi-robot operator control unit
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/701>
-  VIDEO 702 Camera control from gaze
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/702>
-  VIDEO 703 Indoor, urban aerial vehicle navigation
available from <http://handbookofrobotics.org/view-chapter/61/videodetails/703>

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62. Intelligent Vehicles

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This chapter describes the emerging robotics application field of intelligent vehicles – motor vehicles that have autonomous functions and capabilities. The chapter is organized as follows. Section 62.1 provides a motivation for why the development of intelligent vehicles is important, a brief history of the field, and the potential benefits of the technology. Section 62.2 describes the technologies that enable intelligent vehicles to sense vehicle, environment, and driver state, work with digital maps and satellite navigation, and communicate with intelligent transportation infrastructure. Section 62.3 describes the challenges and solutions associated with road scene understanding – a key capability for all intelligent vehicles. Section 62.4 describes advanced driver assistance systems, which use the robotics and sensing technologies described earlier to create new safety and convenience systems for motor vehicles, such as collision avoidance, lane keeping, and parking assistance. Section 62.5 describes driver monitoring technologies that are being developed to mitigate driver fatigue, inattention, and impairment. Section 62.6 describes fully autonomous intelligent vehicles systems that have been developed and deployed. The chapter is concluded in Sect. 62.7 with a discussion of future prospects, while Sect. 62.8 provides references to further reading and additional resources.

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62.1 The Motivation and Approaches to Intelligent Vehicles

An important field of application of robotics has emerged in the last 20–25 years which is centered on the automobile, named *intelligent vehicles*. The automobile has been one of the most important products of the twentieth century. It has generated an enormous industry and has given individuals a freedom of movement that has completely changed our way of life. Indeed, the automobile has been a key factor in the large change in the way our urban societies are structured. Today, there are more than 800 million vehicles on the planet, and this number is expected to double in the next 10 years. This challenge has led to the development of an active research domain with the ultimate goal of automating the typical tasks that humans perform while driving. An intelligent vehicle is defined as a vehicle enhanced with perception, reasoning, and actuating devices that enable the automation of driving tasks such as safe lane following, obstacle avoidance, overtaking slower traffic, following the vehicle ahead, assessing and avoiding dangerous situations, and determining the route. The overall motivation for building intelligent vehicles has been to make motoring safer, and more convenient and efficient.

Approaches to this problem revolve about three main architectures [62.1], according to the degree of autonomy they aim for (Fig. 62.1):

- a) Driver-centric approaches are built around the idea of having a human in the loop supervising the functions of the vehicle.
- b) Network centric-approaches assume that vehicles can share information with other vehicles or the infrastructure.

- c) Vehicle-centric approaches aim to build fully autonomous intelligent vehicles with no human in the loop.

62.1.1 Brief History

Futurama was an exhibit at the 1939 World Fair designed by Norman Bel Geddes that presented a possible model of the world 20 years into the future (1959–1960) with automated highways. The exhibit was sponsored by the General Motors Corporation and was characterized by its vision of automated highways. Technological development in support of this vision began in the late 1940s and early 1950s, with pioneering efforts by RCA Laboratories and GM Research. By 1960, GM had tested full-scale cars driving automatically on test tracks, with lane tracking, lane changing and car following functions automated. The goal of these efforts was the development of an automated highway system (AHS). In the 1960s, a key effort was research and development under the leadership of Fenton and his team at The Ohio State University [62.2]. During these years, vehicles were developed to test steering and speed controllers. Runs were accomplished at the Transportation Research Center (TRC) grounds, using active sensing (a live wire imbedded in the roadway) and with steering control done with analog feedback controllers. In Japan, research on automated highway systems was started in the early 1960s in the Mechanical Engineering Laboratory (MEL) and the National Institute of Advanced Industrial Science and Technology (AIST). The automated driving system in 1960s employed a combination of an inductive cable

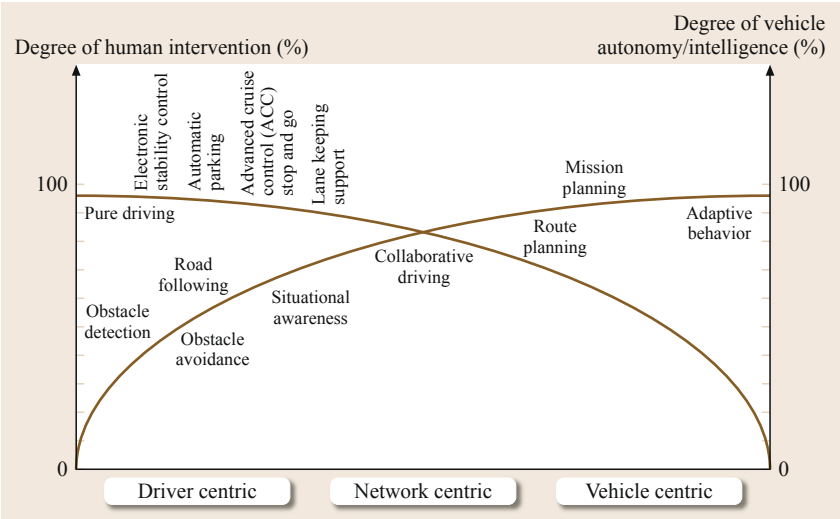


Fig. 62.1 Architectures for autonomous vehicles (after [62.1])

embedded under a roadway surface and a pair of pickup coils at the front bumper of a vehicle for lateral control, and it was a cooperative system between vehicle and infrastructure. In addition to the free agent, a rear-end collision avoidance system between two automated vehicles based on roadway vehicle sensors was developed. The automated vehicle drove up to 100 km/h on a test track in 1967 [62.3].

The history of intelligent vehicles developed further over the ensuing decades. Although the first ideas were born in the 1960s, the level of maturity of the technology at that time did not allow pursuit of the original goal of implementing fully autonomous all-terrain, all-weather vehicles. The first documented prototypes of such vehicles were fielded by a few groups in the military arena in the mid 1980s [62.4–6]. The initial stimulus that triggered these innovative ideas was provided by the military sector, which was eager to provide complete automation to its fleet of ground vehicles.

Testing of autonomous vehicles on real roads in a real environment was one of the most important milestones in the history of intelligent vehicles. In Germany, in the beginning of the 1980s *Dickmanns* and his team equipped a Mercedes-Benz van with cameras and other sensors. For safety reasons, initial experiments in Bavaria took place on streets without traffic. Since 1986 the robot car *VaMoRs* from the same group manages to drive all by itself, since 1987 at speeds up to 96 km/h. A number of these capabilities were also highlighted in the European PROMETHEUS Project. (for example, [62.7])

This happened in the mid to late 1990s. Figure 62.2 shows the first motor vehicles that pioneered the development of intelligent vehicles. In the summer of 1995, the Carnegie Mellon Navlab group ran their *No Hands Across America* experiment [62.8]. They demonstrated automated steering, based solely on computer vision,

over 98% of the time on a 2800 mile trip across the United States. At the same period the EU funded the first large and ambitious project for autonomous car navigation (the EUREKA Project *Prometheus*) involving the major European car constructors and research institutes. In the scope of this project, UBM (Bundeswehr Universität Munich) fielded a vehicle that was demonstrated on a 1758 km-trip from Munich to Copenhagen and back. The vehicle was able to drive autonomously for 95% of the trip. The car suggested and executed manoeuvres to pass other cars. Unlike later robot cars, this car located itself on the current road and followed it until instructed otherwise. It did not localize itself in global coordinates and could drive without a global positioning system (GPS) and road maps as found in a modern automotive navigation systems. The vehicle used dedicated purpose-built computers and hardware.

A different approach was followed by VisLab at the University of Parma within the Argo project. The passenger car that was designed and developed was based on a low-cost approach. An off-the-shelf Pentium 200 MHz personal computer (PC) was used to process stereo images obtained from low-cost cameras installed in the driving cabin. The vehicle was able to follow the lane, locate obstacles, and – when instructed – change lane and overtake slower vehicles. The main milestone of this project was the successful test of the Argo vehicle on a tour of Italy of more than 2000 km called *Millemiglia in Automatico*, in which the vehicle drove itself for 94% of the total distance. Another low-cost approach was developed at INRIA in 1995 for its *dual mode* system, in which a small dedicated electric vehicle was able to park itself autonomously using only ultrasonic sensors and a linear camera.

Through the years, many demonstrations have been held showing the public the capabilities of autonomous vehicles, and by extension, underlining the sensor capabilities at the autonomous driving demonstrations. One of the most comprehensive highway-based demonstrations was held in 1997 on I-15 in San Diego, USA, and showed the capabilities of cars, buses, and trucks in various automated highway scenarios. The demonstration (called Demo'97) was organized by the National Highway Systems Consortium. The key technologies were lane-following using roadway imbedded magnets, roadway laid radar-reflective stripes or using lane markers with vehicle mounted cameras; car following using laser or radar, with or without help of inter-vehicle communication. Scenario maintenance was accomplished by either total preplanning and timing, or by GPS and map-based triggering, or by situation-based triggering [62.9, 10].

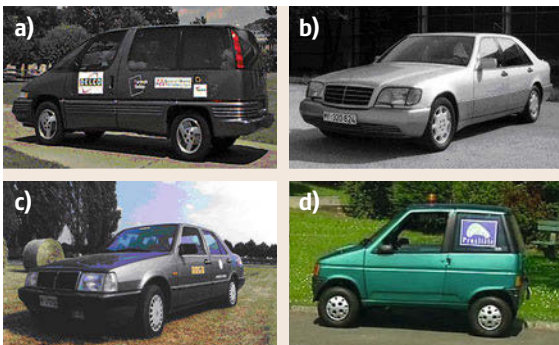


Fig. 62.2a–d Pictures of pioneering autonomous vehicles (a) NAVLAB, (b) UBM, (c) Argo, and (d) Ligier-INRIA electric vehicles

The Demo'97 was followed by a number of demonstrations around the world, notably in Japan, Holland, France, and the US. In each case, not only were state-of-the-art technologies demonstrated, but the public was informed about what to expect in future cars.

In November 2000, the demonstration *Demo 2000 Cooperative Driving* was organized by the National Institute of Advanced Industrial Science and Technology in Tsukuba, Japan. Several platooning scenarios were accomplished by five automated vehicles in the enclosed test field. This platoon of five automated vehicles performed stop-and-go operations, platooning, splitting into two platoons demonstrating an exit ramp, merging into one platoon from two platoons imitating highway traffic at a ramp, and passing by the last vehicles. Furthermore, obstacle detection, platoon leaving, and joining tasks were accomplished. Autonomy was guaranteed by inter-vehicle communication. In addition, vehicles were equipped by differential global positioning system (DGPS) to assure localization by the laser radar to detect obstacles and to measure the relative position between the vehicles. Vehicles of Demo 2000 did not communicate with the infrastructure i. e., road-to-vehicle communication except DGPS. These automated vehicles were autonomously driven by exchanging information through inter-vehicle communication [62.11].

Current research initiatives are oriented towards the development of intelligent vehicles in realistic scenarios. However, until recently, primarily due to legal issues, full autonomy had not yet been set as the ultimate goal. The automotive industry had set as its primary goal the need to equip vehicles with supervised systems and – more generally – advanced driving assistance systems (ADAS) instead of automatic pilots. In other words, the driver was still in charge of running the vehicle, but the driver and vehicle were monitored by an electronic system that detects possibly dangerous situations and reacts by either warning the driver in due time, or taking control of the vehicle in order to mitigate the consequences of the driver's inattention. In spite of the aforementioned legal issues, the ultimate goal has now shifted towards developing self-driving systems and a number of automotive manufacturers have announced such cars in the market by model year 2020. Concurrently, departments of transportation worldwide which have been primarily interested in social, economic, or environmental objectives aimed at enhancing fuel efficiency, road network usage, and improving quality of life in terms of mobility have now shifted their attention to the possibility of mixed traffic on the road, consisting of regular vehicles driven by people and autonomous vehicles [62.12].

Different approaches and research goals have evolved internationally. The USA has pushed for fully autonomous vehicles which could be commercialized, Europe has focused on ADAS systems and public transportation applications, clean vehicles, and free-service autonomous vehicles (Sect. 62.7). This contrast is illustrated by the differences in scope and objectives between US funding schemes and competitions (e.g., DARPA challenges, Google cars) and European projects (e.g., Prometheus, Carsense, Prevent, Inter-safe).

The good results obtained by ADAS in the automotive arena in recent years has induced the military sector to give a new vigorous push to the original ideas of automating its fleet of ground vehicles. The Defense Advanced Research Projects Agency (DARPA) launched the Grand Challenge in 2003, a race for autonomous vehicles that had to travel for more than 200 km in unstructured environments. This unprecedented challenge attracted a large number of top-level research institutes and helped the scientific community take a considerable step forward.

In 2005 the DARPA Grand Challenge required autonomous driving in a rough terrain desert scenario with no traffic, obstacle types known in advance, and few if any road markers on a course predefined by 2935 GPS points [62.13]. Five cars (maximum speed 40 km/h) completed the 211 km desert course, with Stanford's Stanley winning the challenge in 6 h 54 min. Figure 62.3a–b shows photographs of the top two finishing vehicles. The reader is referred to [62.14] for the technical details of the DARPA Grand Challenge.

Following the Grand Challenges, the 2007 DARPA Urban Challenge was performed in *emulated* city traffic and saw the return to urban vehicles [62.15]. Autonomous ground vehicles competed to win the Urban Challenge 2007 prize by accomplishing an approximately 60 mile urban course area in less than 6 h with moving traffic. The autonomous vehicle had to be built upon a full-size chassis compared to production type vehicles and must have a documented safety report. The autonomy capability demonstrated in forms of a complex set of behaviors by obeying all traffic regulations while negotiating with other traffic and obstacles and merging into traffic. The urban driving environment challenged autonomous driving with some physical limits such as narrow lanes, sharp turns, and also by the daily difficulties in a daily urban driving such as congested intersections, obstacles, blocked streets, parked vehicles, pedestrians, and moving vehicles. The winner of the Urban Challenge was Tartan Racing, a collaborative effort by Carnegie Mellon University and the General Motors Corporation, with their vehicle *Boss*, a heavily modified Chevrolet Tahoe. The

second place finisher was the Stanford Racing Team with their entry *Junior*, a 2006 Volkswagen Passat. Figure 62.3c–d shows photographs of the top two finishing vehicles. In May 2011, The Netherlands Organization for Applied Scientific Research TNO, together with the Dutch High Tech Automotive Systems innovation program (HTAS), organized the Grand Cooperative Driving Challenge (GCDC) in The Netherlands. The 2011 GCDC focused on cooperative adaptive cruise control (CACC). Nine international teams participated in the challenge [62.16].

In 2010, the University of Parma's VisLab Intercontinental Autonomous Challenge [62.17–19] further pushed the boundaries by having four driverless vehicles (Fig. 62.3e) drive autonomously 15 000 km from Parma, Italy to Shanghai, China. A more recent example is the Google driverless car (Fig. 62.3f): a fleet of autonomous vehicles which by 2012 had driven more than 480 000 km autonomously. Google has demonstrated fully autonomous driving in dense urban California traffic, utilizing vision-based systems and Google Street View. This activity, repeated in a number of cities generated extensive public interest and led to the belief that autonomous vehicles will be available for public use in the near future. This has been a major factor leading three US states (California, Nevada, and Florida) to approve laws permitting driverless cars. A number of car manufacturers have announced models to come to market by 2020.



Fig. 62.3a–f 2005 Grand Challenge vehicles: (a) Stanley (1st), (b) Sandstorm (2nd), 2007 Urban Challenge vehicles, (c) Boss (1st), (d) Junior (2nd), (e) VisLab and (f) Google vehicles

62.1.2 Benefits of Intelligent Vehicles

Having intelligent vehicles running on our road networks would bring a number of social, environmental, and economical benefits. An intelligent vehicle able to assess the driving scenario and react in case of danger would allow up to 90% of traffic accidents that are caused by human errors to be eliminated, thus saving human lives. According to the World Health Organization an estimated 1.2 million people worldwide are killed each year, and about 40 times this number injured, due to traffic accidents.

At the same time, vehicles able to drive at high speeds and very close to each other would decrease fuel consumption and polluting emissions; furthermore they would also increase road network capacity. Vehicles communicating with a ground station could share their routes and be instructed to reroute in order to maintain a smooth traffic flow. Vehicles that can sense and obey speed limits or traffic rules would reduce the possibility of misinterpretation and antisocial driving behavior.

Fully automatic vehicles would also offer a higher degree and quality of mobility to a larger population, including young, old, or infirm individuals, reducing the need even for a driving licence. Finally, the availability of vehicles that could drive themselves would increase the quality of mobility for everyone, turning personal vehicles into taxis able to pick up people and take them to their final destination in total safety and comfort, enabling people to dedicate their driving time to their preferred activities.

However, this full application of intelligent vehicles is far from being complete, since unmanned vehicle technology is still under development for many other applications. The automation of road vehicles is, perhaps, the most common everyday task that attracts the greatest interest from the industry. However, other domains such as agricultural, mining, construction, search and rescue, and other dangerous applications in general, are looking to autonomous vehicles as a possible solution to the issue of the ever-increasing cost of personnel. If a vehicle could move autonomously on a field to seed, or enter a mined field, or even perform dangerous missions, the number of individuals put at risk would drastically decrease and at the same time the efficiency of the vehicle itself would be increased due to a 24/7 operational schedule. The key challenge for intelligent vehicles is safety; accidents must not occur due to automation errors and there is zero tolerance to human injury and death.

This chapter focuses on road and traffic applications of intelligent vehicles, which are catalyzing the interest of the automotive industry, car makers, and providers of automotive technologies.

62.2 Enabling Technologies

The basic sensing and actuation technologies for intelligent vehicles are readily available on the market. The key challenge to integrating new technologies is heavily dependent on the control strategies associated with the sensor data processing and reasoning. Automated systems must consider all subsystems in a vehicle, including the interaction of the technology with the driver. Key drivers for the new technologies in an intelligent vehicle are the desired applications. Solutions are developed on the premise that the system must satisfy the requirements of the application with the minimum level of technology.

Intelligent vehicle applications require the following:

- The position, and kinematic and dynamic state of the vehicle
- The state of the environment surrounding the vehicle
- Access to digital maps and satellite data
- The state of the driver and occupants
- Communication with roadside infrastructure or other vehicles.

62.2.1 Vehicle State

Position localization is a key technology for intelligent vehicles. The position of the vehicle must be known if the vehicle is to be controlled along a particular trajectory. To control an intelligent vehicle to perform applications such as collision avoidance or automatic lane changing requires knowledge of the kinematic and dynamic states of the vehicle. Standard robotics techniques for position, kinematics, and dynamics are used in intelligent vehicle applications (Chap. 34). Encoders are mounted on the steering column and the tail shaft. Vehicle heading, speed, and acceleration can be computed from the encoders using standard techniques (Chap. 24).

To execute the trajectories in an intelligent vehicle a number of techniques are used. In many current applications of fully automated vehicles, the trajectories are fixed with limited choices at intersections. To execute the trajectories, the vehicles simply follow markers such as an antenna (a wire carrying an alternating current), magnets, or passive transponders such as radio frequency identification (RFID) tags that are imbedded in the road or simple painted lines. In more advanced navigation systems, the vehicle generates trajectories in a map stored in its memory and localizes itself with respect to this map in order to execute them. This localization can be done using absolute positioning through

a combination of global navigation satellite systems (GLS), vehicular kinematic states, and inertial navigation. Alternatively, position localization can be done by relative localization using local markers such as visual landmarks. (For specific reference to earlier mobile robot landmark navigation see Chap. 46.)

In order for the vehicle to execute trajectories, it needs to control the speed and the steering of the vehicle (Fig. 62.4). Modern vehicles now incorporate electronic control units to control the acceleration (motor torque and possibly gearbox and clutch), the braking (electric or electrohydraulic brake control), and the steering angle (electric power assistance), and it is, therefore, quite easy to implement trajectory control of the vehicles [62.20]. The safety of these critical functions remains a challenge, and is usually solved through redundancies in the sensors, actuators, and control units.

62.2.2 Environment State

Sensing the state of the environment surrounding the vehicle is a critical aspect of intelligent vehicle applications. The most difficult function for intelligent vehicles is road scene understanding. This includes locating key landmarks: the road, other vehicles, pedestrians, traffic signals, road signs, and other unstructured obstacles. A more difficult challenge is speed control following the detection of an event in the road scene. Com-

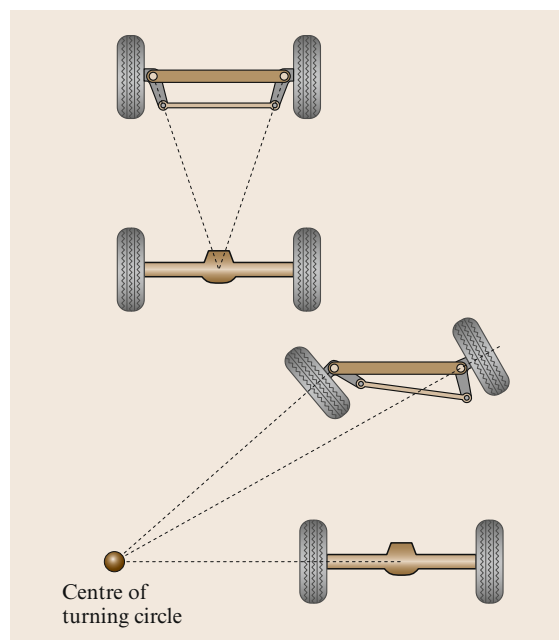


Fig. 62.4 Ackerman steering model

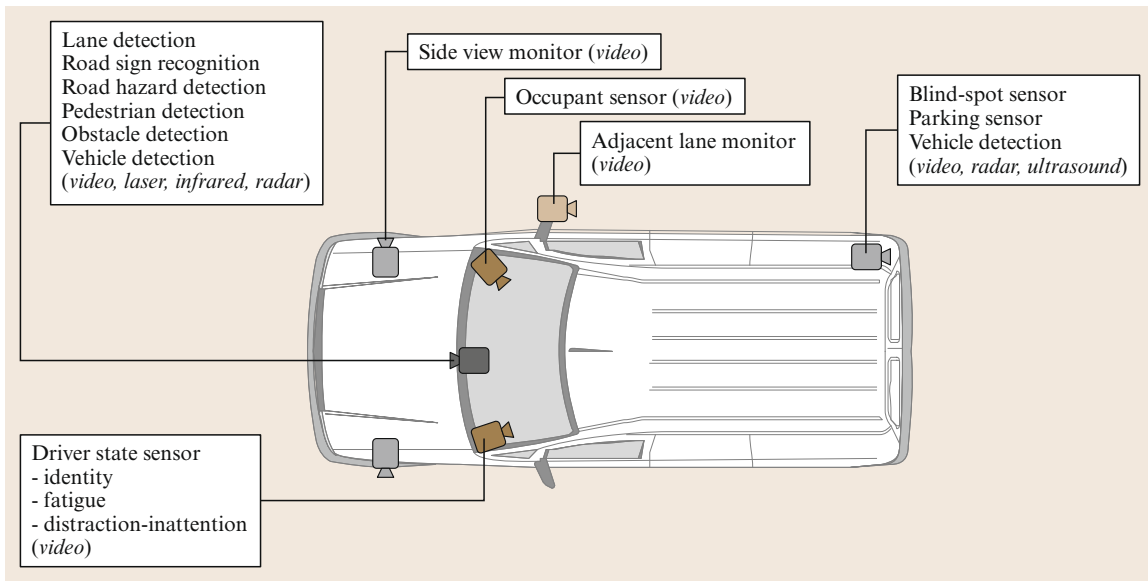


Fig. 62.5 Environment state sensing

mon sensors are infrared [62.21], ultrasound [62.22], radar [62.23], laser range finders [62.24], and computer vision, which continually scan the environment, as shown in Fig. 62.5. Radar is generally used for obstacle detection at a distance, while infrared and ultrasound are used for close proximity obstacle detection. Laser ranging and image processing are used to more robustly recognize the road scene under various weather conditions. Certain road scene conditions such as road signs and traffic lights can only be understood using vision sensing. Sensor fusion is commonly used in intelligent vehicle applications, due to the complementarity of heterogeneous sensor modalities; this can greatly improve perception, for instance, between monocular vision and radar/laser sensors. Sensor fusion (Fig. 62.5) is critical technology for intelligent vehicles and constitutes a wide and active research field for both research teams and automakers (Chap. 35) (Fig. 62.6).

Using such sensors it is possible to map the environment surrounding the vehicle and then, using techniques such as simultaneous localization and mapping (SLAM) (Chap. 46), generate the complex maneuvers needed for parking or for obstacle avoidance.

62.2.3 Digital Maps and Satellite Data

Other additional sensing is generally delivered by global positioning technologies (for example, GPS) to map the vehicle position and refer it to a description of the world known a-priori. This mapping procedure may also be very precise in some areas (like cross coun-

try roads) and may be particularly noisy in others (like downtown areas). To fix issues related to multi-path measurements and to fill gaps when the GPS signal is missing, inertial measurements units (IMU) are generally used together with GPS.

Combining GPS with stored digital maps creates a wide variety of intelligent vehicle applications [62.27]. Map data can greatly assist in the problem of road scene interpretation, map data can improve lane detection quality, help deal with the problems when sensors such as cameras do not work, e.g., in sunlight, at dusk, or dawn. Digital maps are widely

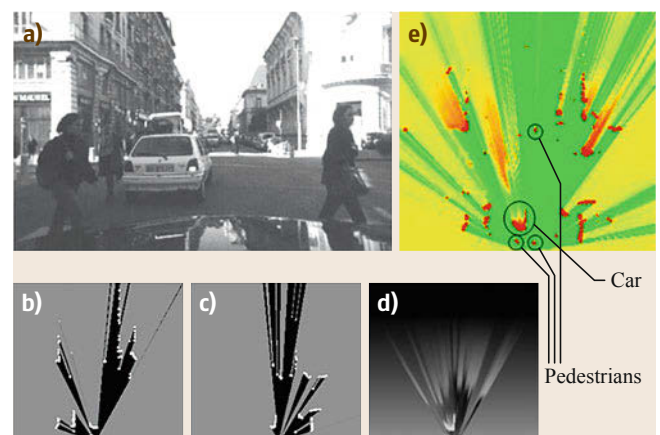


Fig. 62.6a–e Multi-sensor fusion on a Toyota/INRIA experimental vehicle (after [62.25, 26]). (a) Urban scene as seen from a car, (c) occupancy grids, (d) lidar, (e) occupancy grid from a stereo camera, (b) fused data and detected objects

used in commercial navigation systems for route guidance [62.28] and are updated frequently. Such systems will be improved when real-time updating of the map will occur due to the availability of traffic information [62.29]. Additional functionalities to be added include curve approach warnings [62.30], curve speed control [62.31], traffic sign information, and speed limit information [62.32], as well as predetermining an appropriate heading of the headlights in curved and hilly roads.

62.2.4 Driver State

Additionally an intelligent vehicle needs to understand the driver state, if it is to give appropriate warnings or take action. Vision sensors [62.33] can monitor a driver's attentiveness and fatigue by observing the direction of the driver's gaze and eyelid behavior. In an emergency, knowledge of the position of the driver's head as well as all other occupants' position and posture can assist in the safe deployment of airbags. Also, after an accident, observing the state of the driver and other occupants could be useful for the dispatch of emergency services to the accident scene.

62.2.5 Communication

Communication technologies enable interesting applications of intelligent vehicles. Allowing vehicles to communicate with each other and with the highway offers the prospect of vast improvements in the safety and efficiency of the road system. Applications include intersection collision avoidance, emergency braking, and sharing of road and traffic condition information.

The basic communication modes are distinguished as:

- Vehicle to/from roadside infrastructure
- Vehicle to vehicle.

Dedicated short-range communications (**DSRC**) have been set up to from the vehicle to infrastructure communications to support traveler information, commercial applications (toll/parking fee collection, in-vehicle advertising), and safety applications (intersection collision avoidance, approaching emergency vehicle warning, and rollover warning) [62.34].

DSRC is a wireless protocol specifically designed for intelligent transportation systems. It is a subset of **RFID** technology, working in the 5.9 GHz band (US) or 5.8 GHz band (Japan and Europe). It is generally implemented with a dedicated protocol, uses short messages, and works in direct line of sight over short ranges (10–1000 m).

Specific applications are being developed to test a broad variety of potential safety and mobility uses of the systems including:

- Warning drivers of unsafe conditions or imminent collisions.
- Warning drivers if they are about to run off the road or speed around a curve too fast.
- Informing system operators of real-time congestion, weather conditions, and incidents.
- Providing operators with information on road capacity for real-time management, planning, and provision of road advisories to drivers.

For intelligent vehicles safety-related applications using **DSRC** include:

- Stopped vehicle or obstacle avoidance of obstacles on highways.
- Merging assistance from a slow incoming lane into a crowded road.
- Intersection safety and collision warning systems (with or without traffic lights).
- Establishing and maintaining convoys/platoons.

In a vehicle-based intersection collision warning system, each vehicle approaching the intersection generates a message. The message includes the vehicle's location, direction of travel, and the intersection location. This information is based on the **GPS** position and available map data base. Various strategies to predict driver intention are also being studied, and if available this information is also broadcast. Any other vehicle approaching the intersection can calculate the possibility of a collision and will generate an appropriate warning for its driver.

There numerous other possible applications. These include:

- Notification of the presence or approach of an emergency vehicle
- Notification of construction activity
- Local multi-vehicle sensor fusion to provide better global maps and situation awareness
- Energy saving applications (platooning, energy management for HEVs in stop and go traffic).

The USA, since 1999, and the EU, since 2008, have located spectrum in the 5.9 GHz band for wireless **DSRC** systems for vehicular safety and intelligent transportation system applications. The standards for **DSRC** in the US are IEEE 802.11p, finalized in 2010, and wireless access in vehicular environments (**WAVE**) (IEEE 1609), still in draft status as of July 2010. The 802.11p standard is derived from the 802.11A wireless LAN standard and thus provides a fairly easy and inexpensive route to produce communication electronics

and hardware. These standards provide network and application support, as well as sufficient range and data rates, for both V2V and V2I communication applications.

In addition to wireless communication standards, the development of standardized message sets and data definitions in the US has occurred in the SAE J2735 standards process.

The **WAVE** standard supports two types of devices, the roadside unit (**RSU**), and the on-board unit (**OBU**). The **RSU** would typically be a service provider deployed on the roadside that would provide map data like the geometric intersection data (**GID**) message. If it is connected to a traffic light it could also provide signal phase and timing (**SPaT**) messages. Both message types are defined in SAE Standard J2735 [62.35]. The **OBU** is responsible for receiving data from **RSUs** and generating and receiving safety messages that relay information about the vehicle's current state. Many investigations of the utility and capabilities of these

standards exist [62.36] and large-scale testing is underway in the US within the *Connected Vehicle* program.

For vehicle-to-infrastructure communications [62.37], a communication protocol architecture is currently being specified by the ISO-SAE Technical Committee 204 Working Group 16 [62.38]. This protocol architecture is known as communication access for land mobiles (**CALM**) [62.39] and is being implemented in Europe under the cooperative vehicle infrastructure systems (**CVIS**) integrated project [62.40]. **CALM** is based on IPv6 protocols developed by the Internet Engineering Task Force (**IETF**) [62.41], particularly the network mobility (**NEMO**) protocol, which allows sessions to be maintained between an in-vehicle internet protocol (**IP**) network and the Internet backbone using any type of available media (3G, general packet radio service (**GPRS**), Wi-Fi, WiMax, M5, **DSRC**, satellite, etc.). For vehicle-to-vehicle applications, systems that support ad-hoc networking are still in early stages.

62.3 Road Scene Understanding

Perception plays a key role in any robotic application. In the case of intelligent vehicles, the perception task is referred to as road scene understanding. It involves using different sensors (described in Sect. 62.2) combined with automatic reasoning, in order to create a synthetic representation of the environment around the vehicle. The knowledge base accumulated by this task is then used either to issue warnings to the driver in the case of advanced driving assistance systems (**ADAS**) or to control vehicle actuators in the case of complete autonomous driving. A complete and precise description of the state of the surrounding environment is the key factor that allows the reduction of the number of false and missed alarms and provides the basis for smooth automatic driving. Needless to say, the perception of an outdoor environment – even if partially structured – is a challenging problem not only due to the intrinsic complexity of the driving environment itself, but also due to the impossibility of controlling many environmental parameters. Figure 62.7 shows examples of day/night, sun/streetlight illumination, temperature, poor visibility, rain/snow, and different meteorological conditions, which in general are impossible to control and have to be faced by sensing devices.

The research community is addressing the issue of providing vehicles with robust and precise perception of the state of the environment from two different perspectives. One approach is to provide vehicles with ever-increasing sensing capabilities and processing power aimed at the provision of powerful onboard intelligent

systems; [62.42]. An alternative approach is to use road infrastructure as an active component capable of communicating with all vehicles and sharing information on road conditions in real time [62.43]. Indeed, these

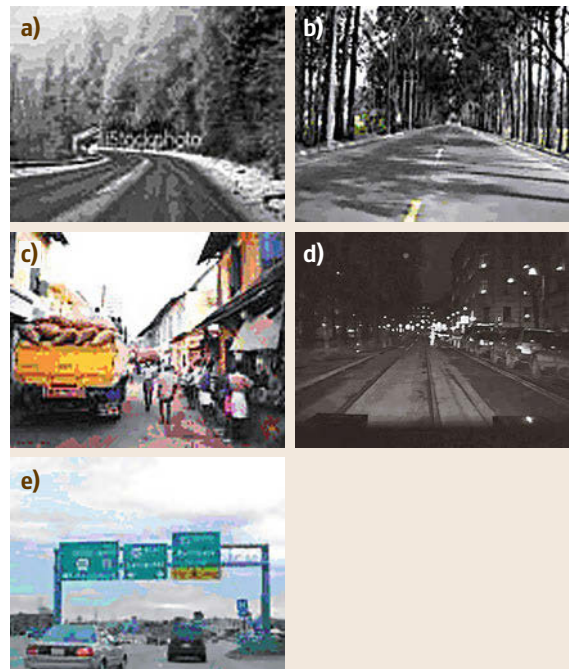


Fig. 62.7 Typical range of road scenes that intelligent vehicles must handle

two perspectives can also be merged to provide a mixed solution to safely control a vehicle and in dynamic environments [62.43].

The task of road scene understanding may be addressed differently, depending on the availability of an intelligent infrastructure and on other players exhibiting cooperative behavior. The task of understanding the state of the environment can be simplified through the availability of information coming from other sources, thereby limiting the need to perform a robust and complete sensing onboard each vehicle. Helpful information could come from the infrastructure itself (for example, road conditions and geometry, number of lanes, visibility, road signs, or even real-time information such as traffic-light status or traffic conditions) or other players (such as the presence of the vehicle with precise position, speed, and direction). The players may also carry real-time information gathered by and shared with other players.

Although research is currently focused on both intelligent vehicles and intelligent infrastructures, the first generation of production intelligent vehicles will have to rely primarily on their own sensing capabilities, since the availability of information coming from other sources such as the infrastructure and other vehicles will take a while to be deployed in real-world situations. In fact, in order to be of practical use, intelligent roads must cover a large proportion of a country, and simultaneously cooperative intelligent vehicles must also be sufficiently widespread. It is important to note that the investment in intelligent infrastructures and intelligent vehicles comes from different sources: mainly from governmental institutions for the former, and vehicle owners for the latter.

The information that is owned by the infrastructure itself and that could be made available to the vehicles includes:

- Precise geometry of the lane/road
- Road signs
- Status of traffic lights.

On the other hand, the infrastructure can also assess and deliver real-time data such as:

- Road conditions
- Visibility
- Traffic conditions.

Another important piece of information that needs to be gathered by intelligent vehicles is the presence of other road players, such as:

- Vehicles
- Vulnerable road users (pedestrians, motorcycles, bicycles).

Although it could be assumed that sometime in the future all vehicles will be equipped with active systems that allow them to be safely avoided by other vehicles, it is quite improbable that pedestrians and bicycles will have similar equipment; their presence will need to be detected using onboard sensors only. The same consideration also applies to obstacles that may unexpectedly be found on the road, or to temporary situations such as roadwork; if a vehicle needs to cope with the unexpected, then it needs to have the capability to assess the situation in real time with its own sensors.

This is why onboard sensing is of paramount importance for future transportation systems; vehicle-to-vehicle and vehicle-to-infrastructure communications may help and improve the sensing, but a complete sensor suite must also be installed on our future vehicles. The main challenges in road environment sensing are examined below.

62.3.1 Road/Lane Tracking

Many vehicle prototypes have been equipped with lane detection and tracking systems, starting from the very first implementations in the early 1980s [62.4–6]. Indeed, in this case computer vision plays a basic role; although generally the road can also be detected with laser scanners [62.24], the only generic technology able to detect lane geometry and lane markings with high precision is computer vision. Most lane tracking approaches have focused on detecting lane markings and exploiting structure in the environment, such as the parallelism of the left and right lane markings, the invariance of road width, or the widely used flat-road assumption. These assumptions were mainly used to overcome the problem of having a single camera (a choice driven by cost). Some systems use stereo vision to detect lane markings and are able to work without such constraints. The problem of lane tracking in highway situations is basically a solved problem – with commercial systems being deployed in passenger and

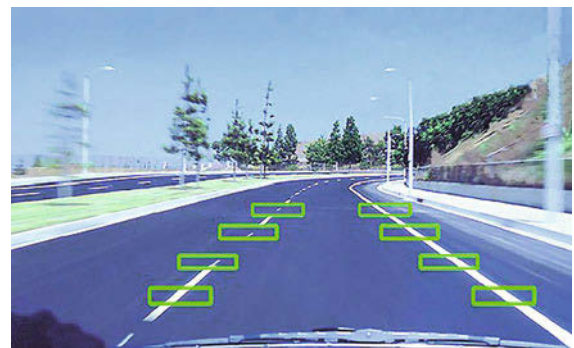


Fig. 62.8 Lane detection

commercial vehicles. A survey and evaluation of the deployed lane tracking technologies is available [62.44]. An example of the typical output of a commercial lane tracker is shown in Fig. 62.8.

However, such systems cannot guarantee that lane detection systems will work with 100% reliability; these systems typically work with 95–99% reliability. Therefore, lane tracking systems are only being used in lane departure warning systems, since no failures can be tolerated for autonomous driving. Efforts are underway to develop algorithms that will tolerate a variety of driving conditions, and push the 100% reliability boundary [62.44, 45],  VIDEO 836.

Vision-based lane tracking systems depend on lane markings, which are not always present. In these cases it is often not enough to track the lane or road's limits. Instead it is necessary to build a local representation of the road's shape and traversability. This local map can be built using SLAM-like techniques (Chap. 46), and can classify parts of the map as either static or dynamic [62.46]. Alternative approaches aim to classify 3-D points obtained from laser scanners or stereo cameras as belonging to the road or not [62.47]. The output of the road detection function is a continuously updated representation of the *navigable space* in front of the vehicle (Fig. 62.9).

62.3.2 Road Sign Detection

Another fairly straightforward use of computer vision is road sign detection and understanding. Road signage is deliberately structured to aid human drivers. Road signs use a set of well-defined shapes, colors, and patterns. The signs are placed at consistent heights and positions in relation to the road. Therefore, reading road signs is an achievable task for computer vision. Detection is done using a collection of shape and/or color detection schemes [62.48, 49]. After the detection and localization phase, recognition takes place. Normally this task is performed by pattern-matching techniques such as image cross-correlation, neural networks, or

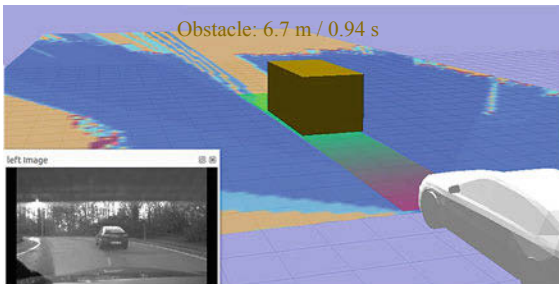


Fig. 62.9 Instantaneous representation of the navigable space in front of the vehicle (after [62.25])

support vector machines, since the possible set of road signs is limited and well defined. Figure 62.10 illustrates the concept of a speeding warning system based on speed sign detection. The challenge for research work in this area lies in the robustness of detection and the reliability of classification of signs. Most automotive companies have systems under development, e.g., Siemens [62.50]. See video on speed sign detection  VIDEO 838.

62.3.3 Traffic-Light Detection

Color and pattern matching are also the key techniques used for the detection of traffic lights [62.51]. Although the detection of traffic lights is not overly complex, this application hides one further aspect that makes vehicular applications difficult: besides the correct localization and recognition of a signal, special care has to be taken in checking the signal position and orientation on the road/lane since that signal may not be addressed to the current vehicle. This is particularly true in downtown intersections at which many traffic lights are visible at the same time; in this case the vehicle must have the capability to select the correct traffic signal that must be obeyed. Some experiments have been undertaken with active traffic signals, able to emit the status of the traffic light using radio frequencies [62.52]. This involves additional infrastructure; at this stage vision seems to be the only simple viable solution.

62.3.4 Visibility Assessment

One of the key challenges is the detection of fog. The meteorological visibility distance is defined by the International Commission on Illumination (CIE) as the distance beyond which a black object of an appropri-

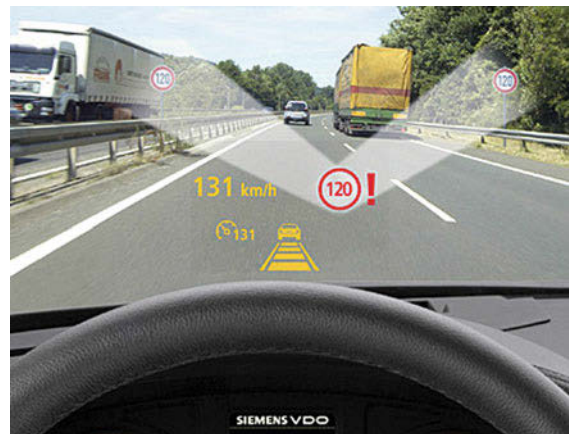


Fig. 62.10 Road sign detection for speed warning application

ate size is perceived with a contrast of less than 5%. Different techniques for measuring this parameter – and thus detect foggy conditions – have been implemented [62.53]. Although many of the methods use vision, there are also efficient alternatives – generally used in fixed locations such as airports and traffic-monitoring stations – based on the use of multiple scattering lidar. The main challenge of using vision to estimate visibility is that a moving vehicle generally cannot rely on a specific reference point/object/signal at a specific distance.

62.3.5 Vehicle Detection

The detection of vehicles has been addressed using a large variety of sensor technologies, ranging from vision to lidar, from radar to sonar.

Despite being different in shape and color, vehicles share the same characteristics and feature a large size and reflective material. The position of vehicles is predictable once a rough indication of the road/lane position is available. Vehicles, in fact, can be suc-

cessfully detected by many different sensors independently [62.55–57]. Figure 62.11 shows a vision-based vehicle detection system.

Nevertheless, although the solution to this problem seems straightforward, each sensor has its own domain of application and its own challenges. Vision is generally powerful, but may fail in low visibility and bad-illumination scenarios (night or tunnels) or in heavy traffic conditions when vehicles may occlude each other. Vision in the infrared domain (thermal imaging) is able to detect vehicles with a high confidence since vehicle tires and mufflers generally exhibit high temperatures and are, therefore, easily detected in the image. However, parked vehicles, trailers, and even vehicles which have just started to move are colder than running vehicles and, therefore, less visible. Lidar is generally robust, but has decreased sensitivity in adverse weather conditions. Radars, while cheap, can suffer from bias in lateral measurements due to the presence of other nearby reflecting objects. Finally, sonars are applicable only for very short distances. The research challenge is to implement multisensor fusion robustly. A common approach is to fuse vision with radar [62.58].

Vehicle detection is often performed by grouping together data that are believed to belong to a same object, this often implies using some kind of similarity metric based in distance and other relevant features such as color, and texture, etc. An alternate approach is taken by *model based* techniques, which scan scene data trying to match models from a pre-existing catalog – e.g., geometric descriptions, part collections. Finally, *grid-based* approaches do not directly model objects themselves, but the evolution of the properties in a regular decomposition of the space (Fig. 62.12) [62.54].



Fig. 62.11 Vehicle detection – lane and range position

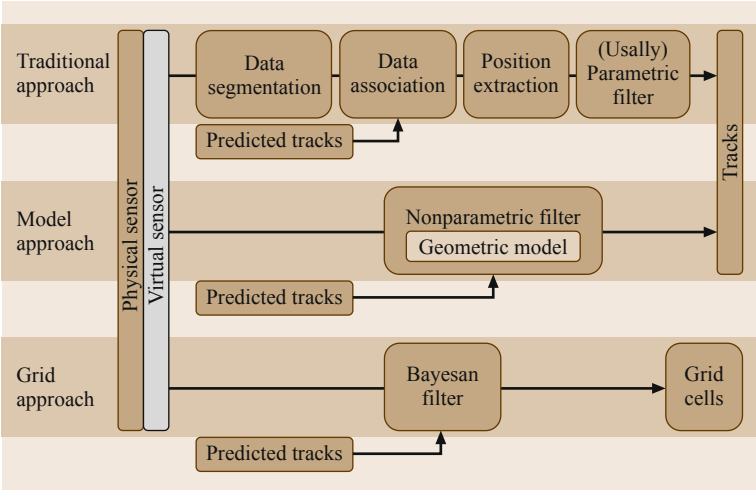


Fig. 62.12 Three alternative approaches to vehicle detection and tracking (after [62.54])

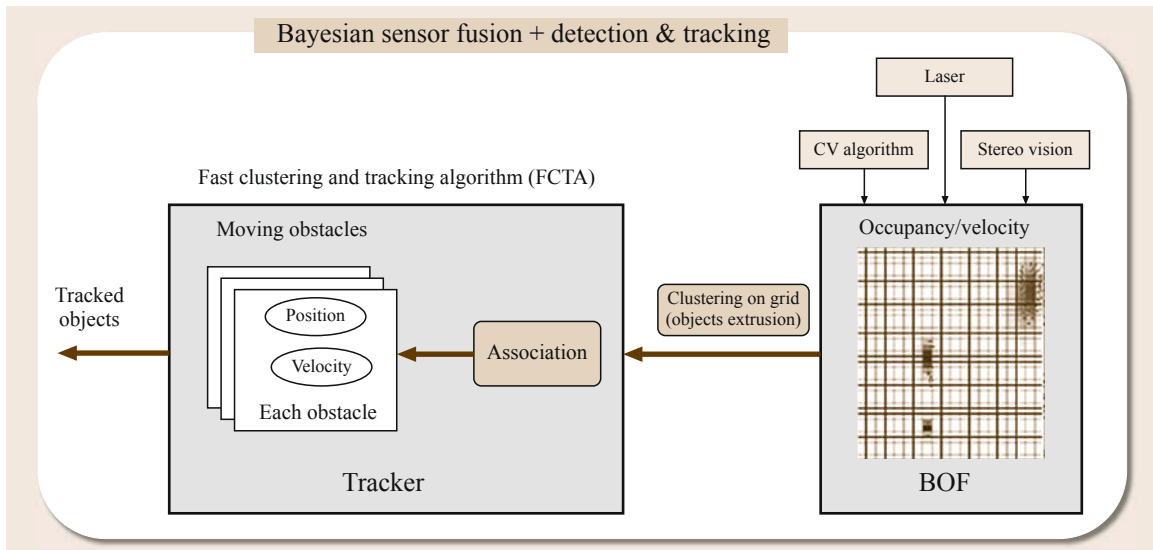


Fig. 62.13 Grid-based detection and tracking (after [62.59])

One of the main problems in tracking is *data association*: finding the correspondence between sensor readings and tracked objects. Tracking approaches differ in the way they solve this problem from the *nearest neighbor*, which just assigns the observation to the closest object to multi-hypothesis tracking (MHT), which maintains a representation of the different association hypothesis for several time steps – pruning is necessary for tractability. An increasingly popular alternative is the use of grid-based approaches, which do not attempt to explicitly represent objects during the iterative grid updates while taking into account all the possible associations with cells in a given neighborhood. This approach leads to postponing as long as possible the object detection and data association steps [62.54]. Refer to Fig. 62.13 for an example of grid-based tracking. [VIDEO 420](#) shows the predictive capabilities of the Bayesian occupancy approach [62.59].

62.3.6 Pedestrian Detection

The detection of vulnerable road users (pedestrians and bicycles) is one of the most difficult tasks for intelligent vehicles. The appearance of a pedestrian is challenging: a pedestrian shape can change greatly within a few

tens of milliseconds; there are no clear invariants in color, texture, or size, and no assumptions can be made about posture, speed, or the visibility of parts of the human body such as the head. Machine learning methods have been successfully applied to this problem [62.24, 42, 48, 60]. The focus is on achieving greater reliability and reduction in false alarms through improved vision algorithms [62.61]. However, the detection of vulnerable road users is one of the most relevant research topics worldwide since a great number of benefits – including insurance reductions – may be achieved once a fully functional pedestrian detector is available on cars. Countermeasures may be activated to reduce the consequences of vehicle–pedestrian accidents, such as the firing of external airbags or the opening of the hood to lessen the impact of a head-on collision. Currently, with all possible technologies under evaluation, no solution seems to offer reliable detection in every scenario: radars are not able to detect pedestrians reliably in crowded scenarios, while vision has the many drawbacks listed above. Even thermal imaging, which – although still very expensive – is generally believed to be one of the most promising technologies, fails in some situations, such as hot summer days and, in general, in high-temperature environments. See video for vision based stereo vision detection [VIDEO 839](#).

62.4 Advanced Driver Assistance

Given the legal liabilities and technical challenges of achieving 100% reliability for autonomous intelligent vehicles, it appears likely that motor vehicles will have

pieces of autonomous functionality added progressively and that cars will eventually evolve into autonomous robots. The perception techniques described earlier can

be used in a variety of ways to make driving safer, more efficient, and less demanding. Individual perception techniques, or combinations of sensing modes, are being used to provide warnings to drivers of dangerous situations. These warnings are being used to prevent collisions in a variety of situations, such as when backing up, when leaving a roadway, into rear ends, on lane changing/merging, with pedestrians, and at intersections.

Developing a collision warning system requires many steps beyond building the perception system. For a typical example, roadway departure warning, the steps followed in a program initiated by the US National Highway Traffic Safety Administration include:

1. Statistical studies. In the United States, crashes involving a single vehicle leaving the roadway are relatively rare, but disproportionately dangerous; approximately 40% of the 40 000 fatal crashes per year in the US are single-vehicle crashes where the vehicle leaves the roadway. The first part of the study looked at the prevalence of those crashes, and determined that this would be a good type of crash to prevent.
2. Causal factors. The second step was to determine the causes of those crashes. Most run-off-road crashes are due to driver factors, such as excessive speed, inattention, or loss of control. This is an important observation, because it means that alerting the driver, or warning of difficult situations, could prevent those incidents. For the fraction of crashes caused by mechanical failure a warning system would not be useful; in this type of crash, mechanical failure is involved in less than 5% of the crashes.
3. Opportunities for intervention. This part of the study set out to determine whether a warning system could be effective, and, if so, how far in advance the warning would have to be given. Given typical road departure trajectories, typical widths of roads and shoulders, and the range of potential steering responses, this task generated requirements for how accurately the system would have to track vehicle trajectory in order to predict a roadway departure.
4. Human factors. Since the system being designed is a warning system, rather than an active control, it is crucial to understand what kinds of warning a driver (who may be distracted or sleepy) would respond to, and how quickly and accurately the response will be. Reaction times vary widely across individuals: using 1 s for reaction time is a fairly standard estimate.
5. Simulator studies. A driving simulator is like an aircraft flight simulator for cars or trucks, with a va-

riety of simulated roads and conditions. Simulator studies were used to test driver response to warnings: directional or nondirectional audio warnings, steering wheel shakes, and combinations. A nondirectional audio cue worked best.

6. System specification development. Based on the preceding steps, in order for a system to be useful, it needs to work at day and night, in almost all weather conditions, it needs to measure vehicle speed, lateral position relative to the road, lateral heading, and roadway curvature, and predict future vehicle trajectories long enough in advance to trigger a warning alarm.
7. Perception and system development. Given those specifications, there are several ways that a perception system could be built to sense the road and the vehicle's trajectory relative to the road. For this particular test, a lane keeping system – the Rapidly Adapting Lane Position Handler (RALPH) was developed and tuned [62.62].
8. Limited tests. The entire system – sensors, processing, driver interface – was built and tested with a limited number of volunteers, and the system tuned and validated.
9. Full-scale operational tests. The system was deployed in test fleets, including long-haul trucks and passenger cars.

62.4.1 Collision Avoidance and Mitigation

The complete cycle from the idea of using perception to prevent crashes, to full system development, took over 10 years in this case. The pure *robotics* part of the system is a crucial element, but is only one piece of the development needed to make a useful product. Some active control has already been assumed by today's vehicles. Antilock brakes have been on the market for many years. Traction control systems which control throttle to stop wheel spin are being introduced. Electronic stability control systems take this the next step further, controlling throttle and individual wheel brakes to help in cornering performance. So, gradually, people are willing to cede some control to very reliable automated systems. We can expect this trend to continue.

Each collision warning type has its own list of specific development challenges, as described below.

Backup Collisions

The sensing challenge is to see relatively small objects, such as fence posts or children's toys, while not picking up false alarms from pavement joints or leaves and debris. The sensors used in today's commercial vehicles are piezoelectric ultrasonic sensors, which are inexpensive [62.22]. However, ultrasonic sensors have

well-known limitations. The challenge of developing low-cost, accurate, reliable sensors remains.

Rear-End Collisions

These are among the most difficult collisions to prevent, with the most challenging sensing conditions. Rear-end collisions often happen at high speeds, requiring long-distance sensing of other vehicles (up to 100 m at US highway speeds, much longer at the high speeds found on some European roads or for the longer braking distances needed for heavy trucks). That in itself is not too demanding a challenge: the sensed objects in this case are relatively large and have high metal components, so radar and lidar are both feasible sensing modes. The biggest range-sensing challenge is sorting out true targets (slow or stopped vehicles) from false targets (overhead signs or bridges, and side lobes from strong reflectors on the side of the road). It is also important to determine if the sensed vehicle is in the same lane as the smart car, or a different lane. Sensing lane markings at such a large distance is a very difficult challenge; merging lane sensing (often done by vision) with obstacle sensing (by a different sensor) and registering the two to within the resolution of a lane is a daunting task. This technology remains under development through industry and government programs [62.63].

Lane-Change/Merge Collisions

In the simplest case, the countermeasure to this kind of collision involves short-range sensing to cover the *blind spots* on the rear corners of a vehicle, where it is difficult to see with mirrors. For passenger cars, this area is quite small, and can be covered with a single sonar or radar. Often, the user interface is a warning light placed in the rear-view mirrors [62.64]; this reinforces good driver behavior of checking mirrors before changing lanes. The sensing challenge for heavy trucks or transit buses is the same as for cars, except that the area not visible in planar mirrors can be much larger. Figure 62.14 shows examples of blind-spot detection for cars and heavy vehicles.

The usual solution is a row of sensors along the side of the vehicle, although scanning lidar or panoramic vision have been used in experimental applications [62.65]. The further complication for lane-change warnings is in high-speed driving, where it is important to look not just adjacently to the vehicle but a long way to the rear, to find overtaking vehicles with high relative speeds. The first commercial product was brought to market in 2007 [62.66].

Pedestrian Collisions

Pedestrians are particularly important to detect, because pedestrians are much more vulnerable than people in



Fig. 62.14 Blind-spot detection

vehicles; as discussed earlier they are also, unfortunately, relatively difficult to detect and very hard to predict. Just detecting a pedestrian is not sufficient. In transit operations, for instance, a bus operates close to pedestrians much of the time. To do meaningful collision warning, it is important to detect the pedestrian, detect their current path, look for cues such as crosswalks or curb edges that modify the probability of the pedestrian's trajectory, and match all of these factors with the predicted trajectory of the vehicle. It is crucial to tune the warning system to produce few false alarms while not missing real alarms. A particularly dangerous situation is pedestrians slipping and falling underneath a bus: these are very dangerous situations, but very difficult to detect in time to warn the driver. For these reasons, automotive manufacturers have worked on products such as night vision to enhance driver perception [62.67]. Car manufacturers are bringing to market products that use a data-fusion approach combined with radar-vision for emergency braking in pedestrian collision situations [62.68].

Other Obstacle Collisions

Vehicles have collisions with many things other than other vehicles and pedestrians, for example, animals (deer, dogs, cats), car parts (tire carcasses, rusted-out exhaust systems), cargo that falls off trucks, construction debris, etc. Warning drivers about these kinds of objects on the roadway is a challenging task. A commercial product for safety systems detects large animals



Fig. 62.15 Animal detection

(Fig. 62.15) using vision and radar sensors [62.69]. A piece of construction timber on the roadway may be large enough to do significant damage to a car, but be small enough to be difficult to see, and be invisible to radar. Some interesting work has been done with high-resolution stereo vision [62.70], with polarimetric radar [62.71], and with high-resolution scanning laser range-finders [62.72]. However, in general, this remains a difficult problem.

Other Actions

Besides warning the driver, there are other actions that an intelligent vehicle can take short of assuming control. If a collision is inevitable, particularly from the side of the vehicle where there is limited crush space, the system can brake and deploy airbags even before physical contact. Of course, such a system would have to be nearly 100% reliable. More simply, if the system senses an imminent front collision, it can preload the power brakes, saving fractions of a second in brake reaction time. The driver must still actuate the brakes, but the onset of hard braking can be much quicker. At 100 km/h, a 0.1 s saving in braking actuation saves approximately 3 m of stopping distance, which can be

the difference between a severe rear-end collision and a much lighter crash. Such systems are being introduced into the high-end market by all the major automotive manufacturers.

Collision Avoidance

The next step beyond emergency braking is an automated system. Such systems have several advantages over a human driver: they have much quicker reaction times, access to sensors such as individual wheel speeds and slips plus external sensors such as radar or lidar, access to individual brake controls and other controls, and so forth. So, if the system had ideal situational awareness, it could, in many cases, do a better job of avoiding a collision than a human could. This is still a very difficult area for implementation, however. First of all, the human has access to higher-level knowledge: the driver may be watching the behaviors of other cars, may make eye contact with pedestrians or drivers, may be watching a policeman directing traffic, etc. So it may be that a maneuver that, to the system, looks like the best way to prevent the collision, is actually the wrong action to take. Secondly, in most countries, as soon as the vehicle takes control there is a shift in the liability for any resulting crash from the driver to the manufacturer. So there is a great reluctance to take active control. An alternative, recently developed approach is to observe the environment state with lidar, and monitor the dynamic vehicle state to determine whether the accident is unavoidable. If the driver can no longer take corrective action, that is, brake or turn away safely, then emergency braking occurs [62.24, 73]. For now, however, active collision avoidance remains a research area, with significant questions of reliability, human factors, and liability.

Traffic Situation Awareness

Traffic situation awareness is a higher level of understanding that is required for decision making in traffic situations. For instance, knowing that a vehi-



Fig. 62.16 A collision warning system for intersection safety implemented on communicating Renault experimental vehicles using the intention/expectation approach (after [62.26])

cle is traveling in the wrong direction along a street is much more informative for estimating the risk of the current situation than knowing its velocity. Thus, traffic situation awareness is emerging as a new area of research effort to understand and reason about the future motion of pedestrians and vehicles. The obtained predictions can then be fed to a motion planning algorithm, which can use this information to minimize collision probabilities [62.74, 75]. Motion models can be used to infer the maneuver intentions of drivers to change lanes [62.76], overtake another vehicle [62.77], make a turn at an intersection [62.78], or comply with the traffic laws at an intersection [62.79]. **VIDEO 566** shows how an embedded Bayesian perception system have been implemented on an experimental vehicle.

Intersection Collisions

Intersection collisions are particularly difficult to prevent because they often involve challenging sensing scenarios. Many of these collisions involve occluded vision, with lines of sight blocked either by large vehicles or by adjacent buildings. They also often involve high closing rates from oblique angles, making it necessary to see a long distance with a very wide field of view. The solution that is usually proposed is to add intelligence to the infrastructure, either in fixed sensing (such as radars looking down each approaching road) or in some kind of radio relay that takes data from approaching smart cars and passes it to other approaching vehicles. All of these solutions are challenging; the large number of intersections makes it difficult to envision any universal solution.

A complementary approach to traffic situation awareness is *risk estimation*, where the objective is to determine how dangerous each potential maneuver is for the vehicle. The classic approach is to use motion models to predict the possible future trajectories for all the dynamic objects in the scene, and then compute the probability of a collision between each possible pair of trajectories for each object. Popular approaches for generating possible future trajectories include rapidly-exploring random trees [62.80], Gaussian processes [62.25, 81], and stochastic reachable states [62.82]. A major limitation of this classic approach to risk estimation is its computational complexity. A recent approach to risk estimation has been proposed, which detects conflicts between the *intentions* of drivers and the *expected* behavior of the vehicle, rather than by detecting collisions between possible future trajectories [62.26, 83] (**VIDEO 822**). More specifically, dangerous situations are identified by comparing *what drivers intend to do* with *what*

drivers are expected to do according to the traffic rules. This formulation of risk reflects the fact that most accidents are caused by driver error [62.84], and matches the intuitive notion that *dangerous* situations are situations where drivers act differently from what is expected of them. This approach can in theory be applied to any traffic situation, but so far has been implemented and tested for scenarios involving cars at road intersections only (Fig. 62.16). Significant research projects are underway in the EU for cooperative vehicle infrastructure projects such as managing intersections [62.85].

Currently, automotive manufacturers are dealing with traffic situation awareness by specifically focusing on discrete driving tasks and typical scenarios. Combining perception with control gives partial automation for specific tasks, such as adaptive cruise control, lane keeping, assisted parking, and slow driving in stop-and-go situations.

62.4.2 Adaptive Cruise Control

Adaptive cruise control (ACC) is the logical extension of standard cruise control to also include keeping a safe distance from the preceding vehicle. If there are no vehicles in front of the smart car, it follows a set speed, as with standard cruise control. If a slower-moving vehicle is in front, an ACC-equipped car will sense the vehicle using radar or lidar, and slow to maintain a safe distance (typically set to a 1.5–2 s following gap). Figure 62.17 shows an illustration of the ACC concept. The sensing challenge for ACC is much easier than the challenge of rear-end collision countermeasures, since ACC systems are only designed to deal with other moving vehicles.

The biggest sensing difficulty for rear-end collision countermeasures is separating stopped vehicles on the road from objects off the road; for ACC this difficulty is bypassed by ignoring all stopped objects. Moving objects are classified as in-lane or out-of-lane based on

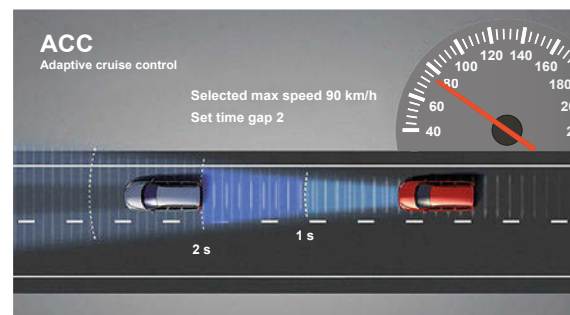


Fig. 62.17 Advanced cruise control (ACC)

a number of heuristics. Often, the smart car's own steering radius is used as an estimate of the road curvature ahead, in order to determine whether vehicles ahead are in the same lane. Since the systems are explicitly sold as *convenience* instead of *safety* systems, they only need to deal with normal situations with relatively low differences in velocity, and they leave the more difficult situations up to the human driver. The human is still alert, controlling the steering, and watching the traffic. These systems are being introduced by all the major car manufacturers.

62.4.3 Stop and Go

Stop-and-go driving assistance (also referred to as low-speed [ACC](#)) is at the opposite end of the speed spectrum, when vehicles creep along in dense traffic. At slow speeds, it is easy to track the vehicle ahead, and to move when it moves, steer when it steers, and stop when it stops. If the traffic accelerates to a modest speed, the stop-and-go system disengages, and the human must assume control of the throttle, brake, and steering. Since the speeds are very slow and the distances are short, many different sensing systems will work, such as stereo vision, radar, and lidar [62.86, 87].

62.4.4 Parking Assistance

Parking assistance is also a low-speed aid. In a typical scenario, the driver initiates the system by pushing a button when driving past an empty parking space. The system measures the length of the space using odometry, measures the positions of the cars in front and in back using short-range sensors, and infers the position of the curb by assuming that the surrounding cars are standard-sized cars parked near the curb [62.88]. Figure 62.18 illustrates parking assistance and fully automatic parking [62.88] ([VIDEO 567](#)).

Once the system is fully engaged, it takes over steering, planning, and executing the ideal parallel park steering sequence. In some systems, the human is still responsible for throttle and brake, again ensuring that the human is alert, watching for encroaching pedestrians or other obstacles. Such a system has been introduced by Toyota [62.89].

62.4.5 Lane Keeping

Lane keeping assistance is the natural extension to road departure warning systems. Given a lane tracking system, it is straightforward to add control of the steering wheel to keep the vehicle centered in its lane [62.4–6]. This has a number of uses. Some cities would like to run transit buses on narrow roadways, for instance the shoulder of highways or through narrow streets in old cities. Automated lane keeping systems using mechanical guideways are in use in several places [62.90]. It is easier and less expensive if such systems can be electronic rather than relying on specially installed mechanical guides. A specific subcategory is precision docking: for a transit bus to pick up a passenger in a wheelchair, either the bus must deploy a special ramp (which is a slow process), or it must pull up to a level dock and leave a very small gap, so that the wheel chair can safely roll on or off. Short-range precision docking systems use either a downward-looking sensor, looking at painted lines or magnetic markers, or a sideways sensor looking at the curb or dock, in order to guide the bus to its parking spot. Finally lane-keeping assistance is a convenience for driving on highways, especially with gusty winds. Honda has released a vehicle equipped with both lane-keeping assistance and adaptive cruise control ([ACC](#)) [62.91]. The danger with such systems is that the driver no longer has an active moment-to-moment role, and may lose concentration or even fall asleep. These systems are not designed for full automation, and still require a driver to handle unusual

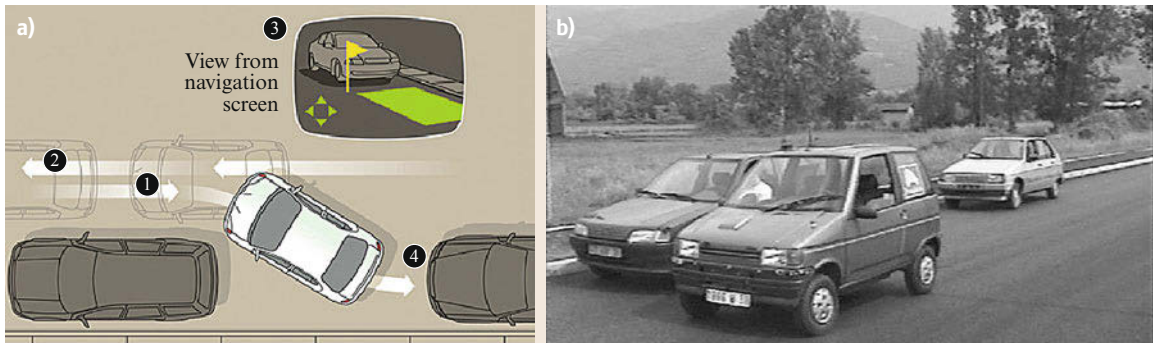


Fig.62.18a,b (a) Parking assistance and (b) fully automatic parking

circumstances. The next stage is to integrate driver state monitoring. If the driver is inattentive, then all automatic systems are disengaged.

62.4.6 Lane Changing

Lane changing assistance is the next extension in partial autonomy. It combines lane keeping and ACC with blind-spot monitoring. If the car can safely overtake a vehicle, then a lane change is undertaken and speed is unchanged [62.92]. Otherwise, the ACC slows the vehicle down. At its simplest, such a driver assistance system can advise a driver whether a lane change can be safely undertaken [62.93]. In its most advanced form the lane change is undertaken completely automatically

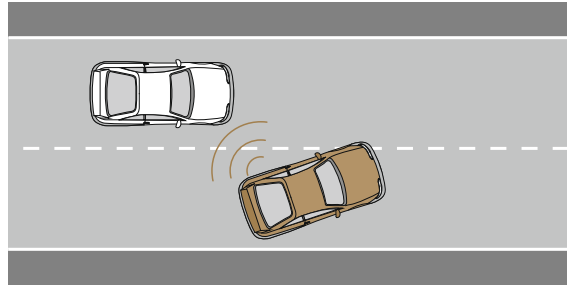


Fig. 62.19 Lane changing – side detection

by the vehicle [62.4]. Such systems require an additional side-facing sensor, typically radar (shown in Fig. 62.19)

62.5 Driver Monitoring

There has been an evolution of thought regarding the role of the driver in intelligent vehicles. The grand goal has been to replace the driver with a fully automated system. As discussed earlier, full automation of intelligent vehicles is still some years away due to system reliability and legal liability reasons. The next step in the development of motor vehicles is partial automation – where individual autonomous functions such as ACC, lane keeping, lane changing etc., are developed. Motor vehicle designers have realized that the driver cannot be removed from the vehicle and must instead be supported by systems onboard a motor vehicle. Over 92% of motor vehicle accidents are caused by driver error [62.94]. It is likely that the next generation of intelligent vehicles will work in the following way:

1. The vehicle will monitor the road scene using the advanced driver assistance system technologies discussed earlier to assess the state of the environment and warn the driver of dangerous situations, e.g., lane departure warnings.
2. The vehicle will also monitor the driver using vision and other physiological sensors to assess the state of the driver. If a driver is fatigued, drowsy, inattentive, distracted, under the influence of drugs, or has an emergency health condition such as heart attack, then accidents can occur. The vehicle warns the driver of dangerous circumstances, e.g., drowsiness warning.
3. For legal liability reasons, intelligent vehicles will not take control, rather the driver will be alerted using visual, audio, or tactile warnings. The vehicle will not perform collision avoidance; rather

collision mitigation will occur through emergency braking.

4. If an accident is unavoidable, the vehicle can autonomously apply emergency braking. To maximize the safety of the occupants in the vehicle, seat belt restraints are tightened and airbags are safely deployed.
5. After an accident has occurred, knowledge about the state of the driver and the passengers is important. If an occupant has been injured, a call to the emergency services can be dispatched automatically by the vehicle.

In all the steps described above monitoring the driver is critical. For future advanced driver assistance systems (ADAS) to work safely the driver should be put in the loop, for example, in lane departure warning systems, it is not possible to determine whether a vehicle departing from a lane is due to driver intention or error. If the state of the driver is being monitored, and the system can detect that the driver's eyes are closed or the driver is looking away from the road, then it can be inferred that the lane departure was involuntary and that a lane departure warning should be given to the driver. For ADAS to be accepted by drivers, the systems should not give false warnings. If the driver is looking directly at the road then lane departure warnings should not be given (or a different subtle warning should be given). Similarly more sophisticated systems, such as lane keeping, should not be engaged unless the driver is fully attentive and has his/her hands firmly on the steering wheel. The key point is that drivers must be fully engaged with and in control of the driving task.

This is a most important consideration in the design of **ADAS** for intelligent vehicles. A good overview of the challenges associated with putting drivers into **ADAS** systems is given in [62.95]

Combining perception with control gives partial automation for specific tasks, such as adaptive cruise control, lane keeping, assisted parking, and slow driving in stop-and-go situations.

62.5.1 Driver Fatigue, Inattention, and Impairment

By directly monitoring the driver using visual sensing opens up the possibility of developing a new class of **ADAS** applications. It is possible to monitor driver state through monitoring signals such as an electrocardiogram (**ECG**), temperature, etc. However, market studies by automobile manufacturers have shown that people do not like to have wires or gadgets attached; driver monitoring must be noncontact and noninvasive. The only solution is to use vision as the sensing medium. The technical challenge to develop a computer vision system that can automatically detect a driver of any age, sex, race, with/without eye or sunglasses, and with/without facial hair is enormous. Recently, significant progress was made with systems being developed that can also detect where a person is looking (gaze direction) [62.33, 96].

Once the driver's state (head position, eye gaze, eye blink rate) can be measured, then **ADAS** applications can be developed. Figure 62.20 shows the output of a commercial driver state detection system. See video for driver distraction, inattention and fatigue detection

 VIDEO 840

Driver Impairment

Safety authorities estimate that as many as 50% of all road accident fatalities are caused by driver impairment



Fig. 62.20 Driver state detection

due to alcohol or drugs [62.97]. Recent research has shown that driver impairment can be detected by sensing abnormal scanning patterns of eye gaze. It promises to open up a new class of **ADAS**. There have been major education and legislative initiatives in many Organization for Economic Cooperation and Development (**OECD**) countries, resulting in a significant reduction in road fatalities. However, the difficult cases (fatigue, distraction, and inattention) have become more prominent. **ADAS** technologies could have a significant impact in further reducing the road toll.

Driver Fatigue

Safety authorities estimate that 25–30% of all road fatalities are caused by driver fatigue [62.98, 99]. Research has shown that there are four visible factors that indicate the onset of fatigue – prolonged eye closure, uncontrolled head moments, drooping eyelids, and reduced eye-gaze scanning. Systems are under development that focus only on eye closure [62.100]; the challenge of fusing all four factors together into a robust algorithm that works for a wide range of drivers remains an open research problem.

Driver Inattention

Safety authorities estimate that up to 45% of all traffic accidents – from minor dents to serious incidents – are caused by driver inattention or distraction [62.101]. Research has shown that if the drivers consistently keep their eyes on the road, then driving becomes a much safer experience [62.102]. All major automotive manufacturers are developing **ADAS** applications that warn the driver if they are distracted from the driving task. More sophisticated **ADAS** under development use the driver's gaze direction to check whether safe driving practices are being followed, for example, did the driver check the side mirror before a lane change was performed? If the driver fails to check the side mirror a warning would be issued. Systems of this type have been demonstrated [62.103].

Driver Workload

The increase in new electronic systems and gadgets that are being installed into today's motor vehicles is also another source of distraction. Questions arise about when and under circumstances should a driver change a compact disc (**CD**) or answer a phone call. Research is underway into the development of workload systems. These systems take into account the vehicle state (speed, acceleration, braking, gear-change yaw rate, etc.) to determine whether information management tasks such as answering a phone call, sending a short message service (**SMS**) message are allowed [62.102]. The next stage of research is to include state infor-

mation about the road scene and the driver. If the car is driving on a country road, and the driver is attentive, then distractive tasks could be allowed and managed. Systems for monitoring the scene for monotony have been combined with fatigue detection systems – and can be combined with information management tasks [62.104]

62.5.2 Driver and Passenger Protection

The automotive industry is moving towards the use of active safety systems such as airbags to complement passive systems such as seat belts. ADAS will play a critical role in active safety systems. In emergency braking or impending rear-end collision situations, seat belts can be pretensioned and airbags primed. Drivers and passengers could be further protected through the development of smart airbags [62.105]. Airbags, while considered an essential part of a modern car, can cause fatalities if the occupant is too close to the airbag, is a child, or is not wearing a seat belt. Smart airbags are dependent on the position of the vehicle occu-

pant's head. The driver state monitoring technologies discussed earlier are an essential component of smart airbags.

62.5.3 Emergency Assistance

The speed at which people are given treatment after a serious accident is critically related to the survival rate of victims. While it is expected that ADAS will lead to a reduction in road accidents, it will not eliminate accidents. Therefore, it is important that automated systems for emergency situations are developed. Systems that use GPS, vehicle state information, and mobile communication systems have been developed that send the world coordinates of the vehicle to emergency authorities after an accident [62.106]. This information can be augmented by using driver monitoring technology to assess the condition of the occupants of the vehicle. Such types of system are referred to as Telematics are currently being tested by major automotive suppliers, including the development of aftermarket products [62.107].

62.6 Towards Fully Autonomous Vehicles

Intelligent vehicles that are fully autonomous can be justified for safety, traffic congestion, and environmental considerations.

62.6.1 Operating Safely

The first problem is safety. As stated earlier, automobile accidents are one of the main causes of human fatalities – on a staggering scale. This is a catastrophe of larger magnitude than all armed conflicts since the beginning of mankind. The most economically advanced countries (OECD) have been able to reduce the number of fatalities significantly through improved technology in vehicles – improved handling, braking, and passive safety. Transport infrastructure has been greatly improved; modern freeways are ten times safer than regular roads [62.108]. However, these improvements appear to be reaching a limit in terms of the number of deaths per million passengers-kilometers, particularly in industrialized countries.

As discussed earlier, motor vehicles are inherently dangerous due to their reliance on human control. Slight errors at high speeds can have catastrophic results. As discussed earlier the most common cause is driver distraction, which leads to improper reaction times or driving actions. Human error also frequently occurs while handling emergency situations. A large percentage of drivers will take improper action in such situations and

produce an accident that could have been avoided by a skilled and attentive driver [62.108]. The best solution to these problems is to remove the driver from the control loop. As discussed earlier, the interim step is to assist the driver to warn him/her in the case of potential danger (e.g., in the case of excessive speed before a dangerous bend or when a car is present in the blind spot while changing lane), or to take over control in emergency situations (e.g., emergency braking in the case of impending collision). For legal liability reasons, until it can be shown that autonomous systems have high integrity and reliability, people must be kept in the loop – in a supervisory capacity.

62.6.2 Traffic Congestion

The success of the automobile also leads to saturation of the road infrastructure, particularly in cities. Each car needs a certain amount of space in order to operate safely. The usual width of roads is 3.5 m in order to accommodate steering imprecision, while vehicles are about 2 m in width. Spacing between vehicles also has to be kept at a safe minimum to prevent collisions during deceleration (this principally depends on driver reaction time). It is usually recommended that the spacing should correspond to a time gap of at least 1.5 s. This spacing leads to a maximum throughput of about 2200 cars per hour per lane, independent of traf-

fic speed. This is not high if we consider that a suburban train can carry about 60 000 passengers per hour on an infrastructure of similar dimensions. Furthermore, high-density car traffic of greater than 2200 cars leads to a breakdown in traffic flow (stop-and-go traffic) and to an increased likelihood of accidents, which can drastically decrease the overall capacity of the system. The solution to this problem also lies in the removal of the driver from the control loop to improve lateral guidance (reduction of the width of lanes) and longitudinal control (with possible time gaps of around 0.3 s, independent of speed) while maintaining traffic safety. Such techniques of automated driving could multiply the throughput of road infrastructure by a factor of 5. This was demonstrated in particular by the work performed in the advanced highway systems (AHS) project in the USA, which led to the demonstration of seven-car platoons running at speeds up to 130 km/h on a dedicated freeway in San Diego with gaps of about 0.5 s [62.109].

Another congestion problem is associated with parking. Every individual vehicle is only used for a small percentage of its total usable life. Most of the time, motor vehicles occupy space very unproductively. Typically, a car requires about 10 m² of space. Usually, parking occurs at the curbside – a space that is very limited in large cities and cannot accommodate all cars of residents and visitors. In parking lots, each car will need four times this amount in order to have access to each individual slot. If a transportation system based on fully automated cars could be developed, people would not need to own cars but could rely on a service such as the one offered by taxis with vehicles that would come on demand and offer a complement to mass transport. This is the concept of the cybercar, which is under development in Europe [62.110].

62.6.3 Environmental Factors

The ever-increasing deployment of passenger and commercial vehicles has led to critical environmental problems of noise and of pollution in the local community. In addition greenhouse-gas emissions have an impact at the global environment level. Recently, automotive manufacturers have been able to reduce emissions of local pollutants drastically; noise in cities is now perceived as the major problem by the inhabitants. At the global level, the generation of CO₂ through the use of fossil fuels is also considered to be a major problem, which will require drastic steps. In the short term, this may lead to limiting the use of vehicles that generate CO₂ above certain levels. In the longer term, this will lead the automotive industry to offer vehicles that run on various forms of energy and to new forms of transportation systems with much higher efficiency. Au-

tomated vehicles running in platoon formations on new infrastructures could form such a system.

62.6.4 The Automobile of the Future

All three challenges are now at the heart of new policies being developed in many countries. These policies concern safety and emissions features in vehicles with a strong push towards advanced safety systems, as was recently seen in Europe with the *Intelligent Car Initiative* [62.111]. At the infrastructure level, there is also a strong push to implement regulation schemes to limit and control the use of road transport and promote alternative and more efficient transport means. In the future, this means that the use of a private automobile will be much more regulated and more integrated with other modes of transport.

The automotive industry might move from an industry of products to an industry of service where anyone can have access to mobility in the most cost efficient way. Both mass transportation and individual transportation would be offered by companies in the most cost-efficient way, respecting local regulations. Companies operating in this service industry could be transit operators, taxi companies, car rental companies, car-sharing companies or even new entrants into the transportation business such as mobile phone companies, which are already familiar with large customer bases and mobility services. Car-sharing operators such as those operating in Germany, Switzerland, Japan, and the USA are likely candidates [62.112]. Figure 62.21 shows a commercial car-sharing operation.

In this context, new types of vehicles such as electric ones and automated driving are being developed because of the decrease in the cost of operation and improvements in safety.

Demonstration projects by Honda and by Toyota have already been put in place along these lines. How-



Fig. 62.21 Car sharing at Toyota

ever, this market is still searching for its operators and business model, as well as the right products [62.110]. Figure 62.22 shows the Honda concept automated car.

There are two distinct trends in the future of automated vehicles. One is with advanced driving assistance, which has spread rapidly since the late 1990s with numerous techniques appearing recently in high-end passenger vehicles and commercial vehicles (buses and trucks). This trend was described earlier in this chapter. The other trend is associated with the arrival of people-movers based on automated guided vehicles (small or large) in specific locations and on dedicated tracks (protected or not).

It is forecast that, in the next 10 years, these two trends will merge, with individual vehicles having dual-mode capabilities: manual (with strong control and assistance) driving on regular roads and fully automatic driving on dedicated zones where no (or few) manual vehicles will be allowed, thereby ensuring smooth and safe operation of automated vehicles [62.110]. This type of vehicle will be perfect for the implementation of mobility services with vehicles that can be called on demand (perhaps through a mobile phone) when and where needed. With the development of such zones, new dedicated infrastructures will be built specifically for these vehicles to go automatically and at high speed from one automated zone to the next. This appears to be the most realistic path for *automated highways* to be realized, since it is now considered nearly impossible to have a smooth evolution from the actual infrastructure with its manual vehicles to one with a majority of fully automated ones. This is one of the reasons why the **AHS** project was canceled in the USA despite a very successful demonstration in 1997.

62.6.5 Automated Vehicle Deployment

As discussed earlier some automated functions are being introduced in production vehicles. Honda and



Fig. 62.22 Automated electric cars by Honda

Toyota have introduced a combination of lateral control (lane keeping assistance using image processing) and longitudinal control (adaptive cruise control using laser and radar sensors) [62.91]. An intelligent parking assist system was introduced recently by Toyota, offering the ability for the car to be parked without the driver using the steering wheel. However, this system does not use sensors: the driver has to position his/her vehicle on the image of the rear camera [62.89]. However, most car manufacturers and some component manufacturers are actively working on the sensors to remove this task from the driver.

Fully automated vehicles without any human intervention or supervision are now appearing in the commercial domain. Automated bus rapid transit (**ABRT**) combines the service quality of rail transit with the flexibility and cost of buses (as shown in Fig. 62.23). Nonautomated bus rapid transit (**BRT**) is already recommended by the World Bank in developing countries as the most efficient mass transport system. By reserving a dedicated lane for bus operation and adding some light infrastructure to facilitate loading and unloading, capacities similar to those of a train (60 000 passengers/h/direction) can be obtained, as has been demonstrated in South America [62.113]. By



Fig. 62.23 Toyota **ABRT** used in **IMTS** Phileas



Fig. 62.24 Cybercars at Schiphol airport, Amsterdam

adding the driving automation on a **BRT**, the system can be made more efficient and safer, as is already the case with automated metros.

The intelligent multimode transit system (**IMTS**) consists of vehicles guided by magnetic markers imbedded in the middle of their dedicated roads. The platoon running function (three electronically linked vehicles running in file formation at uniform speeds) of **IMTS** consists of precisely controlling the speed of all the vehicles in the platoon to be the same at all times [62.114]. In the city of Eindhoven in The Netherlands, multiarticulated buses with several steering axes also run in

automated mode on a dedicated track using magnetic markers [62.115]. These **ABRTs** usually keep a driver in the vehicle, since there is the possibility of reverting to manual mode if need be (such as for an unexpected obstacle or in situations with many pedestrians); however, future plans are for full automation.

ABRT technology can also be found with smaller vehicles, now called cybercars, for on-demand door-to-door operation [62.110]. These vehicles were put into operation for the first time at Schiphol airport (Amsterdam) in December 1997 to move passengers from long-term parking lots to the airport terminal (Fig. 62.24). Since then these cybercars have been further developed, financed by the Information Society Technologies (**IST**) program of the European Commission [62.110]. The long-term future of cybercars may lie with the development of dual-mode vehicles, with a particular emphasis on car-sharing operations [62.112]. Cybercars will have an automatic mode for operation in city centers (restricted to this type of vehicle) and a driver-operated (with assistance) mode for regular roads.  **VIDEO 429** illustrates the cybercar concept. The automobile industry is examining the viability of the development of such vehicles.

In order to match the performance of manually driven vehicles in urban environments, automated vehicles face major technical challenges. In particular, planning a trajectory for a car while avoiding moving and static obstacles remains as an important research challenge. In 2005, the **DARPA** Grand Challenge described at the beginning of this chapter brought together a large number of these researchers to demonstrate the feasibility of automated driving techniques. Five vehicles succeeded in completing the difficult course of 132 miles in the desert in totally autonomous mode. The 2007 **DARPA** challenge focused on multiple vehicles operating simultaneously in an urban environment; this challenge and the subsequent Google cars has certainly shown that automotive products based on autonomous vehicle techniques are becoming closer to market [62.15].

62.7 Future Trends and Prospects

Our cars, trucks, and buses are inevitably getting smarter. The future path is not completely known, and is likely to vary in different locations, but it is becoming widely accepted that there will be no need to drive our cars in the remote future. The time frame is still undefined, but it appears that autonomous cars will populate our highways – perhaps using special lanes– in less than a decade. Governments will not

only have to allow this change, but will have the great opportunity to influence its deployment, for example by increasing the number of dedicated lanes and the benefits that autonomous vehicles will obtain as opposed to less safe driving of manually driven cars.

Four different states in the USA have paved the way for having autonomous vehicles driven on regular

roadways (albeit for testing purposes), moving towards legislation that will make autonomous cars legal on everyday roads. This trend is not only happening in the USA, but also in Europe. Indeed, differences in culture and in driving habits will bring driverless technology into reality in selected locations earlier. Countries in which particularly fast and disrespectful driving is tolerated will make the introduction of autonomous vehicles challenging. Additionally, the safety issues associated with intermingling of autonomous and human driven cars have become critical and extensive investigations are again underway.

Several trends are clear, however. As sensor-equipped vehicles become more common, there will be increasing opportunities to build sensor-friendly technologies into roadways and into vehicles. It is straightforward to reduce the amount of radar clutter on road sides by replacing large metal signs, which are excellent radar reflectors, with nonreflective signs made of plastic or composites. At the same time, it will be desirable to increase the radar cross-section of small vehicles, such as motorcycles, to make them easier for radar-equipped cars to detect. Radar-reflecting licence plates, for in-

stance, would make smaller vehicles stand out more clearly.

The next steps may be to deploy systems that support the active transmission information from infrastructure to vehicle and vehicle to vehicle. Dedicated short-range communications (DSRC) is already in wide use in smart toll collection stations. It is easy to imagine DSRC-equipped vehicles receiving alerts from roadside sensors of upcoming fog, or ice, or congestion. Intelligent vehicles that detect unusual roadway conditions (via radar or lidar, slip detectors, or driver actions such as hard braking) could broadcast that information to all nearby smart vehicles. As market penetration of equipped vehicles increases, the value of such ad-hoc communications nets will go up dramatically.

Vehicle-to-vehicle communications need not be only via radio. Light-emitting diode (LED) brake lights can be pulsed at kilohertz frequencies, well above the bandwidth at which human eyes can detect flicker, but easily received by following vehicles. This would be a straightforward way for a vehicle to tell other vehicles about the onset of hard braking, or other unusual roadway conditions.

62.8 Conclusions and Further Reading

Advances in both the technologies and the algorithmic aspects of developing autonomous vehicles continue. Presently, impressive new systems have been demonstrated (Bertha [62.116] and PROUD [62.117]). In the first case, a Mercedes-Benz S 500 traveled on the historical route between Mannheim and Pforzheim in Germany in August 2013, while the PROUD experiment involved urban driving in open traffic in the inner city of Parma, Italy, and a part of the trip was made with nobody behind the steering wheel ( VIDEO 178).

The general public will become increasingly accustomed to intelligent systems – sensors and communications on vehicles. The only showstopper in the large-scale deployment of robotics technologies in the automobile field is the ability of the industry to deliver the technologies with total safety, which focuses attention on the problems of failsafe systems and their certification. The rail and aerospace industries have solved these problems but in a very different environment. In these industries, the cost of safety for each vehicle can be much higher than in a car or a bus, and the operational environment is also quite different, with professionals operating and maintaining the system. Manufacturers will slowly develop experience in reliability and cost engineering, and governments

will gradually work out liability issues. For these reasons, systems that put the driver in the loop of new automation technologies will be the current focus of development.

Many issues will need to be carefully addressed, including user acceptance, liability, and safety; however, it seems quite probable that this technology will lead to an unprecedented revolution in the field of transportation and people mobility.

For further reading on this topic there are a number of sources that can be recommended:

- Intelligent vehicles survey text [62.9, 10]
- Intelligent transport systems journals (IEEE Transactions on Intelligent Transportation Systems, IEEE Transactions on Vehicular Technology, Transportation Research PART B: Methodology, IEEE Transactions on Intelligent Vehicles)
- Annual conferences (Intelligent Vehicles Symposium, Intelligent Transportation Systems Conference, Vehicular Technology Annual Conference, World Congress on Intelligent Transportation Systems, Intelligent Vehicle Systems Symposium)
- Government resources [62.118–121],
- Magazines (ITS Magazine).

Video-References

-  VIDEO 178 PROUD2013 – Inside VisLab's driverless car
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/178>
-  VIDEO 179 VIAC: The VisLab Intercontinental Autonomous Challenge
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/179>
-  VIDEO 420 Motion prediction using the Bayesian occupancy filter approach (Inria)
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/420>
-  VIDEO 429 Cybercars and the city of tomorrow
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/429>
-  VIDEO 566 Bayesian embedded perception in Inria/Toyota instrumented platform
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/566>
-  VIDEO 567 Inria/Ligier automated parallel parking demo in an open parking area
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/567>
-  VIDEO 822 Collision avoidance at blind intersections using V2V and intention / expectation approach (Inria & Renault)
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/822>
-  VIDEO 836 Lane tracking
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/836>
-  VIDEO 838 Speed sign detection
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/838>
-  VIDEO 839 Pedestrian detection
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/839>
-  VIDEO 840 Driver fatigue and inattention
available from <http://handbookofrobotics.org/view-chapter/62/videodetails/839>

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63. Medical Robotics and Computer-Integrated Surgery

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The growth of medical robotics since the mid-1980s has been striking. From a few initial efforts in stereotactic brain surgery, orthopaedics, endoscopic surgery, microsurgery, and other areas, the field has expanded to include commercially marketed, clinically deployed systems, and a robust and exponentially expanding research community. This chapter will discuss some major themes and illustrate them with examples from current and past research. Further reading providing a more comprehensive review of this rapidly expanding field is suggested in Sect. 63.4.

Medical robots may be classified in many ways: by manipulator design (e.g., kinematics, actuation); by level of autonomy (e.g., preprogrammed versus teleoperation versus constrained cooperative control), by targeted anatomy or technique (e.g., cardiac, intravascular, percutaneous, laparoscopic, microsurgical); or intended operating environment (e.g., in-scanner, conventional operating room). In this chapter, we have chosen to focus on the role of medical robots within the context of larger computer-integrated systems including presurgical planning, intraoperative execution, and postoperative assessment and follow-up.

First, we introduce basic concepts of computer-integrated surgery, discuss critical factors affecting the eventual deployment and acceptance of medical robots, and introduce the basic system paradigms of surgical computer-assisted planning, execution, monitoring, and assessment (surgical CAD/CAM) and surgical assistance. In subsequent sections, we provide an overview of the technology of medical robot systems and discuss examples of our basic system paradigms, with brief additional discussion topics of remote telesurgery and robotic surgical simulators. We conclude with some thoughts on future research directions and provide suggested further reading.

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63.1 Core Concepts

A fundamental property of robotic systems is their ability to couple complex information to physical action in order to perform a useful task. This ability to replace, supplement, or transcend human performance has had a profound influence on many fields of our society, including industrial production, exploration, quality control, and laboratory processes. Although robots have often been first introduced to automate or improve discrete processes such as welding or test probe placement or to provide access to environments where humans cannot safely go, their greater long-term impact has often come indirectly as essential enablers of computer integration of entire production or service processes.

63.1.1 Medical Robotics, Computer-Integrated Surgery, and Closed-Loop Interventions

Medical robots have a similar potential to fundamentally change surgery and interventional medicine as part of a broader, information-intensive environment that exploits the complementary strengths of humans and computer-based technology. The robots may be thought of as information-driven surgical tools that enable human surgeons to treat individual patients with greater safety, improved efficacy, and reduced morbidity than would otherwise be possible. Further, the consistency and information infrastructure associated with medical robotic and computer-assisted surgery systems have the potential to make *computer-integrated surgery* as important to health care as computer-integrated manufacturing is to industrial production.

Figure 63.1 illustrates this view of computer-integrated surgery (CIS). The process starts with infor-

mation about the patient, which can include medical images (computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), etc.), lab test results, and other information. This patient-specific information is combined with statistical information about human anatomy, physiology, and disease to produce a comprehensive computer representation of the patient, which can then be used to produce an optimized interventional plan. In the operating room, the preoperative patient model and plan must be *registered* to the actual patient. Typically, this is done by identifying corresponding landmarks or structures on the preoperative model and the patient, either by means of additional imaging (x-ray, ultrasound, video), by the use of a tracked pointing device, or by the robot itself. If the patient’s anatomy has changed, then the model and plan are updated appropriately, and the planned procedure is carried out with assistance of the robot. As the intervention continues, additional imaging or other sensing is used to monitor the progress of the procedure, to update the patient model, and to verify that the planned procedure has been successfully executed. After the procedure is complete, further imaging, modeling, and computer-assisted assessment is performed for patient follow-up and to plan subsequent interventions, if any should be required. Further, all the patient-specific data generated during the planning, execution, and follow-up phases can be retained. These data can subsequently be analyzed statistically to improve the rules and methods used to plan future procedures.

63.1.2 Factors Affecting the Acceptance of Medical Robots

Medical robotics is ultimately an application-driven research field. Although the development of medical robotic systems requires significant innovation and can lead to very real, fundamental advances in technology, medical robots must provide measurable and significant advantages if they are to be widely accepted and deployed. The situation is complicated by the fact that these advantages are often difficult to measure, can take an extended period to assess, and may be of varying importance to different groups. Table 63.1 lists some of the more important factors that researchers contemplating the development of a new medical robot system should consider in assessing their proposed approach.

Broadly, the advantages offered by medical robots may be grouped into three areas. The first is the potential of a medical robot to *significantly improve surgeons’ technical capability* to perform procedures by

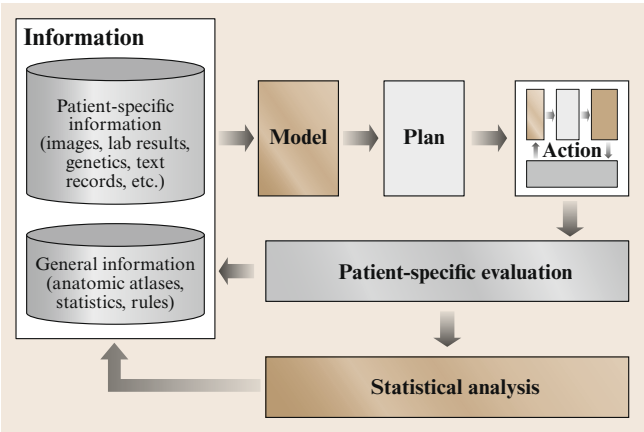


Fig. 63.1 Fundamental information flow in computer-integrated surgery

Table 63.1 Assessment factors for medical robots or computer-integrated surgery systems (after [63.1])

Assessment factor	Important to whom	Assessment method	Summary of key leverage
New treatment options	Clinical researchers, patients	Clinical and trials preclinical	Transcend human sensory-motor limits (e.g., in microsurgery). Enable less invasive procedures with real-time image feedback (e.g., fluoroscopic or MRI -guided liver or prostate therapy). Speed up clinical research through greater consistency and data gathering
Quality	Surgeons, patients	Clinician judgment; revision rates	Significantly improve the quality of surgical technique (e.g., in microvascular anastomosis), thus improving results and reducing the need for revision surgery
Time and cost	Surgeons, hospitals, insurers	Hours, hospital charges	Speed operating room (OR) time for some interventions. Reduce costs from healing time and revision surgery. Provide effective intervention to treat patient condition
Less invasiveness	Surgeons, patients	Qualitative judgment; recovery times	Provide crucial information and feedback needed to reduce the invasiveness of surgical procedures, thus reducing infection risk, recovery times, and costs (e.g., percutaneous spine surgery)
Safety	Surgeons, patients	Complication and revision surgery rates	Reduce surgical complications and errors, again lowering costs, improving outcomes and shortening hospital stays (e.g., robotic total hip replacement (THR), steady-hand brain surgery)
Real-time feedback	Surgeons	Qualitative assessment, quantitative comparison of plan to observation, revision surgery rates	Integrate preoperative models and intraoperative images to give surgeon timely and accurate information about the patient and intervention (e.g., fluoroscopic x-rays without surgeon exposure, percutaneous therapy in conventional MRI scanners). Assure that the planned intervention has in fact been accomplished
Accuracy or precision	Surgeons	Quantitative comparison of plan to actual	Significantly improve the accuracy of therapy dose pattern delivery and tissue manipulation tasks (e.g., solid organ therapy, microsurgery, robotic bone machining)
Enhanced documentation and follow-up	Surgeons, clinical researchers	Databases, anatomical atlases, images, and clinical observations	Exploit CIS systems' ability to log more varied and detailed information about each surgical case than is practical in conventional manual surgery. Over time, this ability, coupled with CIS systems' consistency, has the potential to significantly improve surgical practice and shorten research trials

exploiting the complementary strengths of humans and robots summarized in Table 63.2. Medical robots can be constructed to be more precise and geometrically accurate than an unaided human. They can operate in hostile radiological environments and can provide great dexterity for minimally invasive procedures inside the

patient's body. These capabilities can both enhance the ability of an *average* surgeon to perform procedures that only a few exceptionally gifted surgeons can perform unassisted and can also make it possible to perform interventions that would otherwise be completely infeasible.

Table 63.2 Complementary strengths of human surgeons and robots (after [63.1])

	Strengths	Limitations
Humans	Excellent judgment Excellent hand–eye coordination Excellent dexterity (at natural <i>human</i> scale) Able to integrate and act on multiple information sources Easily trained Versatile and able to improvise	Prone to fatigue and inattention Limited fine motion control due to tremor Limited manipulation ability and dexterity outside natural scale Cannot see through tissue Bulky end-effectors (hands) Limited geometric accuracy Hard to keep sterile Affected by radiation, infection
Robots	Excellent geometric accuracy Untiring and stable Immune to ionizing radiation Can be designed to operate at many different scales of motion and payload Able to integrate multiple sources of numerical and sensor data	Poor judgment Hard to adapt to new situations Limited dexterity Limited hand–eye coordination Limited haptic sensing (today) Limited ability to integrate and interpret complex information

A second, closely related capability is the potential of medical robots to *promote surgical safety* both by improving a surgeon’s technical performance and by means of active assists such as *no-fly zones* or *virtual fixtures* (Sect. 63.2.3) to prevent surgical instruments from causing unintentional damage to delicate structures. Furthermore, the integration of medical robots within the information infrastructure of a larger **CIS** system can provide the surgeon with significantly improved monitoring and online decision supports, thus further improving safety.

A third advantage is the inherent ability of medical robots and **CIS** systems to *promote consistency* while *capturing detailed online information* for every procedure. Consistent execution (e.g., in spacing and tensioning of sutures or in placing of components in joint reconstructions) is itself an important quality factor. If saved and routinely analyzed, the *flight data recorder* information inherently available with a medical robot can be used both in *morbidity and mortality* assessments of serious surgical incidents and, potentially, in statistical analyses examining many cases to develop better surgical plans. Furthermore, such data can provide valuable input for surgical simulators, as well as a database for developing skill assessment and certification tools for surgeons.

63.1.3 Medical Robotics System Paradigms: Surgical CAD/CAM and Surgical Assistance

We call the process of computer-assisted planning, registration, execution, monitoring, and assessment *surgical CAD/CAM*, emphasizing the analogy to manufacturing **CAD/CAM**. Just as in manufacturing, robots

can be critical in this **CAD/CAM** process by enhancing the surgeon’s ability to execute surgical plans. The specific role played by the robot depends somewhat on the application, but current systems tend to exploit the geometric accuracy of the robot and/or its ability to function concurrently with x-ray or other imaging devices. Typical examples include radiation therapy delivery robots such as Accuray’s CyberKnife [63.2] (Accuray, Inc., Sunnyvale, CA), shaping of bone in orthopaedic joint reconstructions (discussed further in Sect. 63.3.2) and image-guided placement of therapy needles (Sect. 63.3.3).

Surgery is often highly interactive; many decisions are made by the surgeon in the operating room and executed immediately, usually with direct visual or haptic feedback. Generally, the goal of surgical robotics is not to replace the surgeon so much as to improve his or her ability to treat the patient. The robot is thus a computer-controlled surgical tool in which control of the robot is often shared in one way or another between the human surgeon and a computer. We thus often speak of medical robots as *surgical assistants*.

Broadly, robotic surgical assistants may be broken into two subcategories. The first category, *surgeon extender robots*, manipulate surgical instruments under the direct control of the surgeon, usually through a teleoperation or *hands-on* cooperative control interface. The primary value of these systems is that they can overcome some of the perception and manipulation limitations of the surgeon. Examples include the ability to manipulate surgical instruments with superhuman precision by eliminating hand tremor, the ability to perform highly dexterous tasks inside the patient’s body, or the ability to perform surgery on a patient who is physically remote from the surgeon. Although setup time is still a serious concern with most surgeon extender

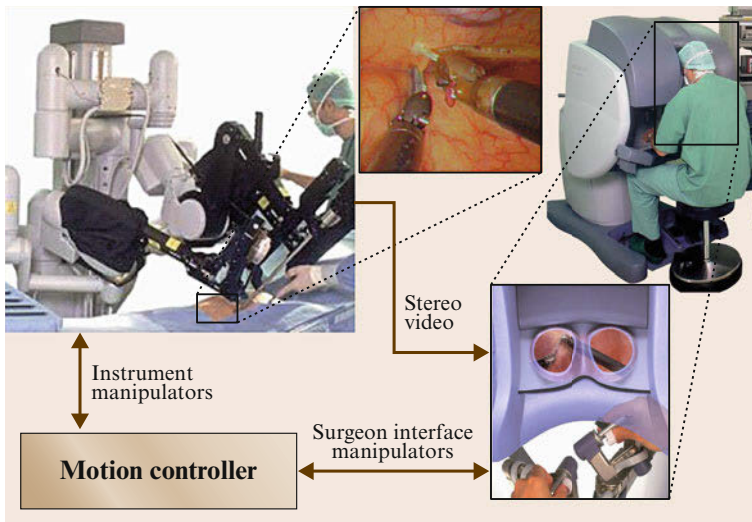


Fig. 63.2 The da Vinci telesurgical robot (after [63.3]) extends a surgeon's capabilities by providing the immediacy and dexterity of *open* surgery in a minimally invasive surgical environment (photos courtesy of Intuitive Surgical, Sunnyvale)

systems, the greater ease of manipulation that such systems offer has the potential to reduce operative times. One widely deployed example of a surgeon extender is the da Vinci system [63.3] (Intuitive Surgical Systems, Sunnyvale, CA) shown in Fig. 63.2. Other examples (among many) include the Sensei catheter system [63.7] (Hansen Medical Systems, Mountain View, CA.), the

Johns Hopkins University (JHU) *Steady Hand* micro-surgery robot [63.4–6] shown in Fig. 63.3 and discussed in Sect. 63.3, the Rio orthopaedic robot [63.8] (Mako Surgical Systems, Ft. Lauderdale, Florida), the DLR *Miro* system [63.9], the Surgica Robotica's *Sergenius* system (Surgica Robotica, Udine), and Titan Medical's *Amadeus* System (Titan Medical, Toronto, Canada).

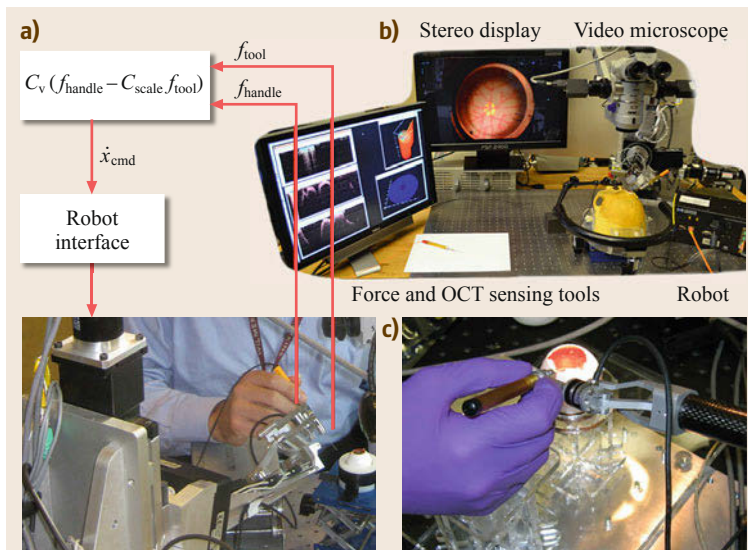


Fig. 63.3a–c The Johns Hopkins *Steady Hand* microsurgical robot (after [63.4–6]) extends a surgeon's capabilities by providing the ability to manipulate surgical instruments with very high precision while still exploiting the surgeon's natural hand-eye coordination. **(a)** The basic paradigm of hands-on compliant guiding. The commanded velocity of the robot is proportional to a scaled difference between the forces exerted by the surgeon on the tool handle and (optionally) sensed tool-to-tissue forces. **(b)** Current laboratory setup, showing the robot, stereo video microscope, stereo display with information overlays, display console for optical coherence tomography (OCT) system, and a sensorized tool. **(c)** An earlier recent version of the Steady Hand robot currently being used for experiments in microcannulation of 100 μm blood vessels

A second category, *auxiliary surgical support robots*, generally work alongside the surgeon and perform such routine tasks as tissue retraction, limb positioning, or endoscope holding. One primary advantage of such systems is their potential to reduce the number of people required in the operating room, although that advantage can only be achieved if *all* the tasks routinely performed by an assisting individual can be automated. Other advantages can include improved task performance (e.g., a steadier endoscopic view), safety (e.g., elimination of excessive retraction forces), or simply giving the surgeon a greater feeling of control over the procedure. One of the key challenges in these sys-

tems is providing the required assistance without posing an undue burden on the surgeon's attention. A variety of control interfaces are common, including joysticks, head tracking, voice recognition systems, and visual tracking of the surgeon and surgical instruments, for example, the Aesop endoscope positioner [63.10] used both a foot-actuated joystick and a very effective voice recognition system. Again, further examples are discussed in Sect. 63.3.

It is important to realize that *surgical CAD/CAM* and *surgical assistance* are complementary concepts. They are not at all incompatible, and many systems have aspects of both.

63.2 Technology

The mechanical design of a surgical robot depends crucially on its intended application. For example, robots with high precision, stiffness and (possibly) limited dexterity are often very suitable for orthopaedic bone shaping or stereotactic needle placement, and medical robots for these applications [63.17–20] frequently have high gear ratios and consequently, low back-drivability, high stiffness, and low speed. On the other hand, robots for complex, minimally invasive surgery (MIS)

on soft tissues require compactness, dexterity, and responsiveness. These systems [63.3, 21] frequently have relatively high speed, low stiffness, and highly back-drivable mechanisms.

63.2.1 Mechanical Design Considerations

Many early medical robots [63.17, 20, 22] were essentially modified industrial robots. This approach has many advantages, including low cost, high reliability, and shortened development times. If suitable modifications are made to ensure safety and sterility, such systems can be very successful clinically [63.18], and they can also be invaluable for rapid prototyping and research use.

However, the specialized requirements of surgical applications have tended to encourage more specialized designs. For example, laparoscopic surgery and percutaneous needle placement procedures typically involve the passage or manipulation of instruments about a common entry point into the patient's body. There are three basic design approaches. The first approach uses a passive wrist to allow the instrument to pivot about the insertion point and has been used in the commercial Aesop and Zeus robots [63.21, 23] as well as several research systems. The second approach mechanically constrains the motion of the surgical tool to rotate about a *remote center of motion (RCM)* distal to the robot's structure. In surgery, the robot is positioned so that the RCM point coincides with the entry point into the patient's body. This approach has been used by the commercially developed da Vinci robot [63.3], as well as by numerous research groups, using a variety of kinematic designs [63.24–26]. Finally, a third approach uses an active external wrist [63.9, 17] and thus supports robot-assisted interventions that do not require a pivot point,

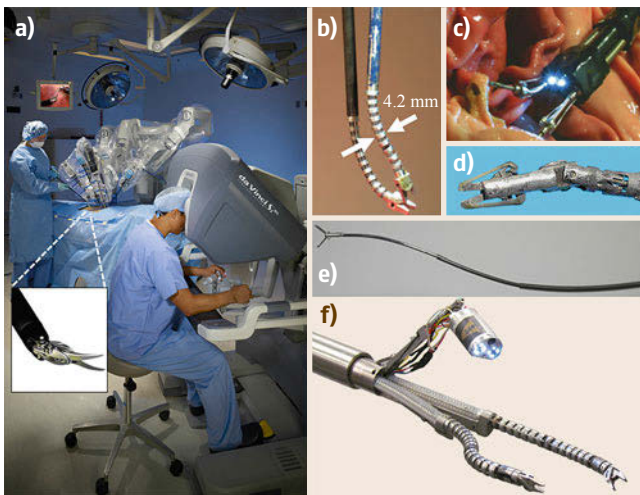


Fig. 63.4a–f Dexterity enhancement inside a patient's body: (a) The Intuitive da Vinci Si system and wrist with a typical surgical instrument (Photos courtesy of Intuitive Surgical) (after [63.3]); (b) The end-effectors of the JHU/Columbia snake telesurgical system (after [63.11]); (c) Two-handed manipulation system for use in endogastric surgery (after [63.12]); (d) five-degree-of-freedom 3 mm wrist and gripper (after [63.13]) for microsurgery in deep and narrow spaces; (e) concentric tube robot (after [63.14, 15]); (f) Columbia/Vanderbilt high dexterity system for single port access surgery (after [63.16])

potentially extending robotic surgery to other field of surgery.

The emergence of minimally invasive surgery has created a need for robotic systems that can provide high degrees of dexterity in very constrained spaces inside the patient's body, and at smaller and smaller scales. Figure 63.4 shows several typical examples of current approaches. One common response has been to develop cable-actuated wrists [63.3]. However, a number of investigators have investigated other approaches, including bending structural elements [63.11], shape-memory alloy actuators [63.27, 28], microhydraulic systems [63.29], and electroactive polymers [63.30]. Similarly, the problem of providing access to surgical sites inside the body has led several groups to develop semiautonomously moving robots for epicardial [63.31] or endoluminal applications [63.32, 33].

Two growing trends **MIS** are natural orifice trans-luminal surgery (**NOTES**) [63.34, 35] and single port laparoscopy (**SPL**) [63.36]: the idea is to get access to the abdominal cavity by using natural orifices and internal incisions (in **NOTES**) or existing human scars (e.g., the navel, in **SPL**). From the mechanical design viewpoint, there is the need to develop deployable surgical instruments or accessorised endoscopes and to combine flexibility (to reach the target) and stability of the platform (to achieve precision). Clashing of instruments and difficulty in triangulation are the main limitations which companies and research groups try to approach [63.37, 38].

The problem of distal operation, already present in **MIS**, is becoming more dramatic in **NOTES** and **SPL** and several solutions for helping surgical tasks requiring triangulation have been developed by different research groups [63.39]. They are based on magnetic fields which can generate an internal force without constraining the internal tool to the access port [63.40–42].

Another significant development in recent years has been the emergence and widespread deployment of three-dimensional (**3-D**) printing and other rapid prototyping technologies for clinically usable medical devices and medical robot components, as well as for construction of realistic patient-specific models [63.43, 44]. This trend has promoted very rapid progress in medical robot design and will be increasingly important in coming years.

Although most surgical robots are mounted to the surgical table, to the operating room ceiling, or to the floor, there has been growing interest in developing systems that directly attach to the patient [63.45, 46], and clinically deployed examples exist [63.47]. The main advantage of this approach is that the relative position of the robot and patient is unaffected if the patient moves. The challenges are that the robot must

be smaller and that relatively nonintrusive means for mounting it must be developed.

Finally, robotic systems intended for use in specific imaging environments pose additional design challenges. First, there is the geometric constraint that the robot (or at least its end-effector) must fit within the scanner along with the patient. Second, the robot's mechanical structure and actuators must not interfere with the image formation process. In the case of x-ray and **CT**, satisfying these constraints is relatively straightforward. The constraints for **MRI** are more challenging [63.48].

63.2.2 Control Paradigms

Surgical robots assist surgeons in treating patients by moving surgical instruments, sensors, or other devices in relation to the patient. Generally, these motions are controlled by the surgeon in one of three ways:

- *Preprogrammed, semi-autonomous motion*: The desired behavior of the robot's tools is specified interactively by the surgeon, usually based on medical images. The computer fills in the details and obtains the surgeon's concurrence before the robot is moved. Examples include the selection of needle target and insertion points for percutaneous therapy and tool cutter paths for orthopaedic bone machining.
- *Teleoperator control*: The surgeon specifies the desired motions directly through a separate human interface device and the robot moves immediately. Examples include common telesurgery systems such as the da Vinci [63.3]. Although physical *master* manipulators are the most common input devices, other human interfaces are also used, notably voice control [63.21].
- *Hands-on compliant control*: The surgeon grasps the surgical tool held by the robot or a control handle on the robot's end-effector. A force sensor senses the direction that the surgeon wishes to move the tool and the computer moves the robot to comply. Early experiences with Robodoc [63.17] and other surgical robots [63.25] showed that surgeons found this form of control to be very convenient and natural for surgical tasks. Subsequently, a number of groups have exploited this idea for precise surgical tasks, notably the **JHU Steady Hand** microsurgical robot [63.4] shown in Fig. 63.3, the Rio orthopaedic robot [63.8] (Mako Surgical Systems, Ft. Lauderdale, Florida) and the Imperial College Acrobot orthopaedic system [63.49] shown in Fig. 63.5c,d.

These control modes are not mutually exclusive and are frequently mixed. For example, the Robodoc sys-



Fig. 63.5a–d Clinically deployed robots for orthopaedic surgery. **(a,b)** The Robodoc system (after [63.17, 18]) represents the first clinically applied robot for joint reconstruction surgery and has been used for both primary and revision hip replacement surgery as well as knee replacement surgery. **(c,d)** The Acrobot system of Davies et al. (after [63.49]) uses hands-on compliant guiding together with a form of virtual fixtures to prepare the femur and tibia for knee replacement surgery

tem [63.17, 18] uses hands-on control to position the robot close to the patient's femur or knee and preprogrammed motions for bone machining. Similarly, the IBM/JHU LARS robot, [63.25] used both cooperative and telerobotic control modes. The cooperatively controlled Acrobot [63.49] uses preprogrammed virtual fixtures (Sect. 63.1.3) derived from the implant shape and its planned position relative to medical images.

Each mode has advantages and limitations, depending on the task. Preprogrammed motions permit complex paths to be generated from relatively simple specifications of the specific task to be performed. They are most often encountered in surgical CAD/CAM applications where the planning uses two- (2-D) or three-dimensional (3-D) medical images. However, they can also provide useful complex motions combining sensory feedback in teleoperated or hands-on systems. Examples might include passing a suture or inserting a needle into a vessel after the surgeon has prepositioned the tip. On the other hand, interactive specification of motions based on real-time visual appreciation of deforming anatomy would be very difficult.

Teleoperated control provides the greatest versatility for interactive surgery applications, such as dexterous MIS [63.3, 21, 26, 50] or remote surgery [63.51, 52]. It permits motions to be scaled, and (in some research systems) facilitates haptic feedback between master and slave systems. The main drawbacks are complexity, cost, and disruption to standard operating room work flow associated with having separate master and slave robots.

Hands-on control combines the precision, strength, and tremor-free motion of robotic devices with some of the immediacy of freehand surgical manipulation. These systems tend to be less expensive than telesur-

gical systems, since there is less hardware, and they can be easier to introduce into existing surgical settings. They exploit a surgeon's natural eye–hand coordination in an intuitively appealing way, and they can be adapted to provide force scaling [63.4, 5]. Although direct motion scaling is not possible, the fact that the tool moves in the direction that the surgeon pulls it makes this limitation relatively unimportant when working with a surgical microscope. The biggest drawbacks are that hands-on control is inherently incompatible with any degree of remoteness between the surgeon and the surgical tool and that it is not practical to provide hands-on control of instruments with distal dexterity.

Teleoperation and hands-on control are both compatible with *shared control modes* in which the robot controller constrains or augments the motions specified by the surgeon, as discussed in Sect. 63.2.3.

63.2.3 Virtual Fixtures and Human–Machine Cooperative Systems

Although one goal of both teleoperation and hands-on control is often *transparency*, i. e., the ability to move an instrument with the freedom and dexterity he/she might expect with a handheld tool, the fact that a computer is actually controlling the robot's motion creates many more possibilities. The simplest is a safety barrier or *no-fly zone*, in which the robot's tool is constrained from entering certain portions of its workspace. More sophisticated versions include virtual springs, dampers, or complex kinematic constraints that help a surgeon align a tool, maintain a desired force, or maintain a desired anatomical relationship. The Acrobot system shown in Fig. 63.5c,d represents a successful clinical applica-

tion of the concept, which has many names, of which *virtual fixtures* seems to be the most popular [63.53, 54]. A number of groups are exploring extensions of the concept to active cooperative control, in which the surgeon and robot share or trade off control of the robot during a surgical task or subtask. As the ability of computers to model and follow along surgical tasks improves, these modes will become more and more important in surgical assistant applications. Figure 63.6 illustrates the overall concept of human-machine cooperative systems in surgery, and Fig. 63.7 illustrates the use of registered anatomical models to generate constraint-based virtual fixtures. These approaches are equally valid whether the surgeon interacts with the system through classical teleoperation or through hands-on compliant control. See also Chap. 43.

Both teleoperation and hands-on control are likewise used in human-machine cooperative systems for rehabilitation and disability assistance systems. Constrained hands-on systems offer special importance for rehabilitation applications and for helping people with movement disorders. Similarly, teleoperation and intelligent task following and control are likely to be vital for further advances in assistive systems for people with severe physical disabilities. See Chap. 64 for a further discussion of human-machine cooperation in assistive systems.

63.2.4 Safety and Sterility

Medical robots are safety-critical systems, and safety should be considered from the very beginning of the design process [63.55, 56]. Although there is some difference in detail, government regulatory bodies require a careful and rigorous development process with extensive documentation at all stages of design, implementation, testing, manufacturing, and field support. Generally, systems should have extensive redundancy built into hardware and control software, with multiple consistency conditions constantly enforced. The basic consideration is that no single point of failure should cause the robot to go out of control or to injure a patient. Although there is some difference of opinion as to the best way to make trade-offs, medical manipulators are usually equipped with redundant position encoders and ways to mechanically limit the speed and/or force that the robot can exert. If a consistency check failure is detected, two common approaches are to *freeze* robot motion or to cause the manipulator to go limp. Which is better depends strongly on the particular application.

Sterilizability and biocompatibility are also crucial considerations. Again, the details are application dependent. Common sterilization methods include gamma

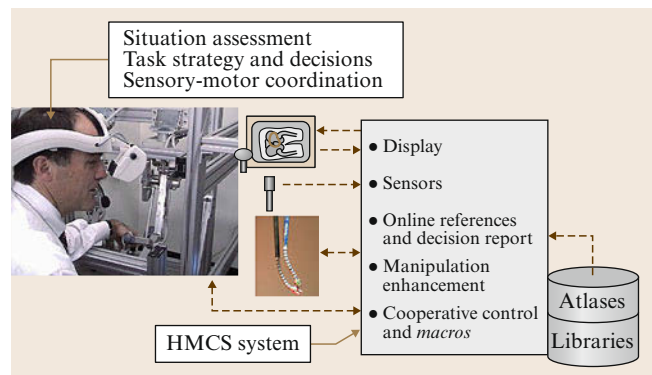


Fig. 63.6 Human-machine cooperative systems (HMCS) in surgery

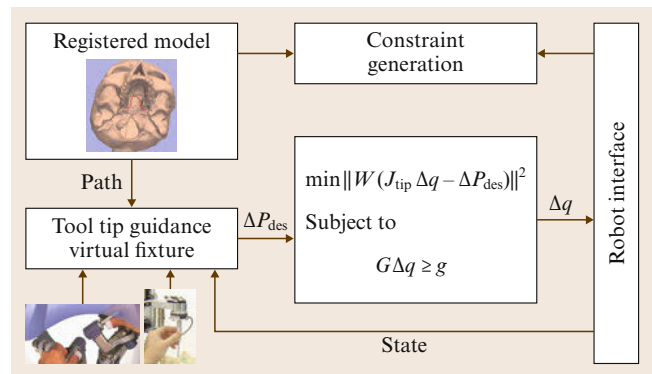


Fig. 63.7 Human-machine cooperative manipulation using constraint-based virtual fixtures, in which patient-specific constraints are derived from registered anatomical models (after [63.53])

rays (for disposable tools), autoclaving, soaking or gas sterilization, and the use of sterile drapes to cover unsterile components. Soaking or gas sterilization are less likely to damage robot components, but very rigorous cleaning is required to prevent extraneous foreign matter from shielding microbes from the sterilizing agent.

Careful attention to higher levels of application protocols is also essential. Just like any other tool, surgical robots must be used correctly by surgeons, and careful training is essential for safe practice. Surgeons must understand both the capabilities and limitations of the robot and of the surgical process as well, since safety is a systemic property. This adds new requirements to training programs, which must include robotic capabilities and nontechnical skills (Sect. 63.3.8). In surgical CAD/CAM applications, the surgeon must understand how the robot will execute the plan and be able to verify that the plan is being followed. If the surgeon is interactively commanding the robot, it is essential that the robot interpret these commands cor-

rectly. Similarly, it is essential that the robot's model of its task environment correspond correctly to the actual environment. The availability of task models is necessary to the development of autonomous execution of robotic gestures as well as the formal verification of task correctness [63.57]. Although careful design and implementation can practically eliminate the likelihood of a runaway condition by the manipulator, this will do little good if the robot is badly registered to the patient images used to control the procedure. If the robot fails for any reason, there must be well-documented and planned procedures for recovery (and possibly continuing the procedure manually).

Finally, it is important to remember that a well-designed robot system can actually *enhance* patient safety. The robot is not subject to fatigue or momentary lapses of attention. Its motions can be more precise and there is less chance that a slip of the scalpel may damage some delicate structure. In fact, the system can be programmed to provide *virtual fixtures* (Sect. 63.2.3) preventing a tool from entering a forbidden region unless the surgeon explicitly overrides the system.

63.2.5 Imaging and Modelling of Patients

As the capabilities of medical robots continue to evolve, the use of computer systems to model dynamically changing patient-specific anatomy will become increasingly important. There is a robust and diverse research community addressing a very broad range of research topics, including the creation of patient-specific models from medical images, techniques for updating these models based upon real-time image and other sensor data, and the use of these models for planning and monitoring of surgical procedures. Some of the pertinent research topics include the following:

- Medical image segmentation and image fusion to construct and update patient-specific anatomic models
- Biomechanical property measurement and modelling for analyzing and predicting tissue deformations and functional factors affecting surgical planning, control, and rehabilitation
- Optimization methods for treatment planning and interactive control of systems
- Methods for registering the *virtual reality* of images and computational models to the *physical reality* of an actual patient
- Methods for characterizing treatment plans and individual task steps such as suturing, needle insertion, or limb manipulation for purposes of planning, monitoring, control, and intelligent assistance
- Real-time data fusion for such purposes as updating models from intraoperative images
- Methods for human-machine communication, including real-time visualization of data models, natural language understanding, gesture recognition, etc.
- Methods for characterizing uncertainties in data, models, and systems and for using this information in developing robust planning and control methods.

An in-depth examination of this research is beyond the scope of this article. A more complete discussion of these topics may be found in the suggested further reading in Sect. 63.4.

63.2.6 Registration

Geometric relationships are fundamental in medical robotics, especially in surgical CAD/CAM. There is an extensive literature on techniques for coregistering coordinate systems associated with robots, sensors, images, and the patient [63.58, 59]. Following [63.59], we briefly summarize the main concepts here. Suppose that we have coordinates

$$\mathbf{v}_A^r = (x_A, y_A, z_A)$$

$$\mathbf{v}_B^r = (x_B, y_B, z_B),$$

corresponding to comparable locations in two coordinate systems Ref_A and Ref_B . Then the process of registration is simply that of finding a function $\mathbf{T}_{AB}(\cdots)$ such that

$$\mathbf{v}_B = \mathbf{T}_{AB}(\mathbf{v}_A).$$

Generally, $\mathbf{T}_{AB}(\cdots)$ is assumed to be a rigid transformation of the form

$$\mathbf{T}_{AB}(\mathbf{v}_A^r) = \mathbf{R}_{AB}\mathbf{v}_A^r + \mathbf{p}_{AB},$$

where $\mathbf{R}_{AB}$ represents a rotation and $\mathbf{p}_{AB}$ represents a translation, but nonrigid transformations are becoming increasingly common. There are hundreds of methods for computing $\mathbf{T}_{AB}(\cdots)$. The most common for medical robotics involve finding a set of corresponding geometric features Γ_A and Γ_B whose coordinates can be determined in both coordinate systems and then finding a transformation that minimizes some distance function $d_{AB} = \text{distance}[\Gamma_B, \mathbf{T}_{AB}(\Gamma_A)]$. Typical features can include artificial fiducial objects (pins, implanted spheres, rods, etc.) or anatomical features such as point landmarks, ridge curves, or surfaces.

One common class of methods is based on the iterated closest-point algorithm of *Besl* and *McKay* [63.60],

for example, 3-D robot coordinates a_j may be found for a collection of points known to be on the surface of an anatomical structure that can also be found in a segmented 3-D image. Given an estimate T_k of the transformation between image and robot coordinates, the method iteratively finds corresponding points b_j on the surface that are closest to $T_k a_j$ and then finds a new

transformation

$$T_{k+1} = \arg \min_T \sum_j (b_j - T a_j)^2.$$

The process is repeated until some suitable termination condition is reached.

63.3 Systems, Research Areas, and Applications

Medical robots are not ends in themselves. As the late Hap Paul often remarked, *the robot is a surgical tool designed to improve the efficacy of a procedure*. (Paul was the founder of Integrated Surgical Systems. Along with William Bargar, he was one of the first people to recognize the potential of robots to fundamentally improve the precision of orthopaedic surgery.)

63.3.1 Nonrobotic Computer-Assisted Surgery: Navigation and Image Overlay Devices

In cases where the role of the robot is placing instruments on targets determined from medical images, *surgical navigation* is often a superior alternative. In surgical navigation [63.61], the positions of instruments relative to the reference markers on the patient are tracked using specialized electromechanical, optical, electromagnetic, or sonic digitizers or by more general computer vision techniques. After the relationships between key coordinate systems (patient anatomy, images, surgical tools, etc.) are determined through a registration process (Sect. 63.2.6), a computer workstation provides graphical feedback to the surgeon to assist in performing the planned task, usually by displaying instrument positions relative to medical images, as shown in Fig. 63.8a. Although the registration is usually performed computationally, a simple mechanical alignment of an image display with an imaging device can be surprisingly effective in some cases. One example [63.62] is shown in Fig. 63.8b.

The main advantages of surgical navigation systems are their versatility, their relative simplicity, and their ability to exploit the surgeon's natural dexterity and haptic sensitivity. They are readily combined with *passive* fixtures and manipulation aids [63.65, 66]. The main drawbacks, compared to active robots, are those associated with human limitations in accuracy, strength, ability to work in certain imaging environments, and dexterity inside the patient's body (Table 63.2).

Because these advantages often outweigh the limitations, surgical navigation systems are achieving

widespread and increasing acceptance in such fields as neurosurgery, otolaryngology, and orthopaedics. Since much of the technology of these systems is compatible with surgical robots and since technical problems such as registration are common among all these systems, we may expect to see a growing number of hybrid applications combining medical robots and navigation.

63.3.2 Orthopaedic Systems

Orthopaedic surgery represents a natural surgical CAD/CAM application, and both surgical navigation systems and medical robots have been applied to orthopaedics. Bone is rigid and is easily imaged in CT and intraoperative x-rays, and surgeons are accustomed to doing at least some preplanning based on these images. Geometric accuracy in executing surgical plans is very important, for example, bones must be shaped accurately to ensure proper fit and positioning of components in joint replacement surgery. Similarly, osteotomies require both accurate cutting and placement of bone fragments. Spine surgery often requires screws and other hardware to be placed into vertebrae without damage to the spinal cord, nerves, and nearby blood vessels.

The Robodoc system shown in Fig. 63.5a,b represents the first clinically applied robot for joint reconstruction surgery [63.17, 18]. Since 1992, it has been applied successfully to both primary and revision hip replacement surgery, as well as knee surgery. Since this system exhibits many of the characteristics of surgical CAD/CAM, we will discuss it in some detail. In the *surgical CAD* phase, the surgeon selects the desired based on preoperative CT images and interactively specifies the desired position of the implant components. In the *surgical CAM* phase, surgery proceeds normally up to the point where the patient's bones are to be prepared to receive the implant. The robot is moved up to the operating table, the patient's bones are attached rigidly to the robot's base, and the robot is registered to the CT images either by use of implanted fiducial pins or by use of a 3-D digitizer to match bone

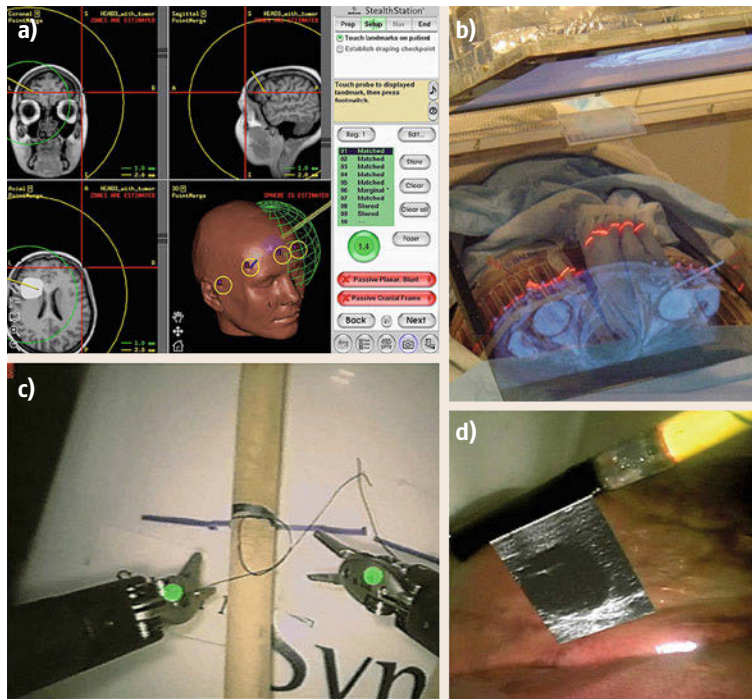


Fig.63.8a–d Information enhancement for surgical assistance. (a) Display from a typical surgical navigation system, here the Medtronic StealthStation; (b) the JHU image overlay system (after [63.62]) uses a mirror to align the virtual image of a cross-sectional image with the corresponding physical position in the patient's body; (c) Sensory substitution display of surgical force information onto da Vinci surgical robot video monitor (after [63.63]); (d) Overlay of laparoscopic ultrasound onto the da Vinci surgical robot video monitor (after [63.64])

surfaces to the CT images. After registration, the surgeon's hand guides the robot to an approximate initial starting position. Then, the robot autonomously machines the desired shape with a high-speed rotary cutter while the surgeon monitors progress. During cutting, the robot monitors cutting forces, bone motion, and other safety sensor, and either the robot controller or the surgeon can pause execution at any time. If the procedure is paused for any reason, there are a number of error recovery procedures available to permit the procedure to be resumed or restarted at one of several defined checkpoints. Once the desired shape has been machined, surgery proceeds manually in the normal manner.

Subsequently, several other robotic systems for joint replacement surgery have been introduced or proposed. The references in Sect. 63.4 provide numerous examples. Notable hands-on guided systems include Rio surgical robot [63.8] (Mako Surgical, Ft. Lauderdale, Florida) and the Acrobot [63.49] system for knee surgery shown in Figs. 63.5c,d. Similarly, several groups have recently proposed small orthopaedic robots attaching directly to the patient's bones [63.45] or completely freehand systems such as the NaviPFS surgical system (Blue Belt Technologies, Pittsburgh, Pa.) which combine surgical navigation with very fast on-off control of a surgical cutter [63.67, 68]. A recent example of a hybrid passive-active robot is [63.69].

63.3.3 Percutaneous Needle Placement Systems

Needle placement procedures have become ubiquitous in image-guided intervention, typically performed through the skin but also through cavities. These procedures fit within the broader paradigm of surgical CAD/CAM, where the process involves use of patient images to identify targets within the patient and planning needle trajectories; inserting the needles and verifying their placement; performing some action such as an injection or taking a biopsy sample; and assessing the results. In most cases, an accuracy of 1–2 mm is acceptable, which is not easy to achieve freehand, because the target is not directly visible, soft tissues tend to deform and deflect, and needles often bend. The procedures typically rely on some form of intra-operative imaging (x-ray, CT, MRI, and ultrasound) for both guidance and verification. The surgical motion sequence typically has three decoupled phases: place the needle tip at the entry point, orient the needle by pivoting around the needle tip, and insert the needle into the body along a straight trajectory. These motions are often performed freehand, with varying degrees of information feedback for the physician. However, passive, semiautonomous, and active robotic systems have all been introduced. Figure 63.9 shows several clinically deployed systems for needle placement.

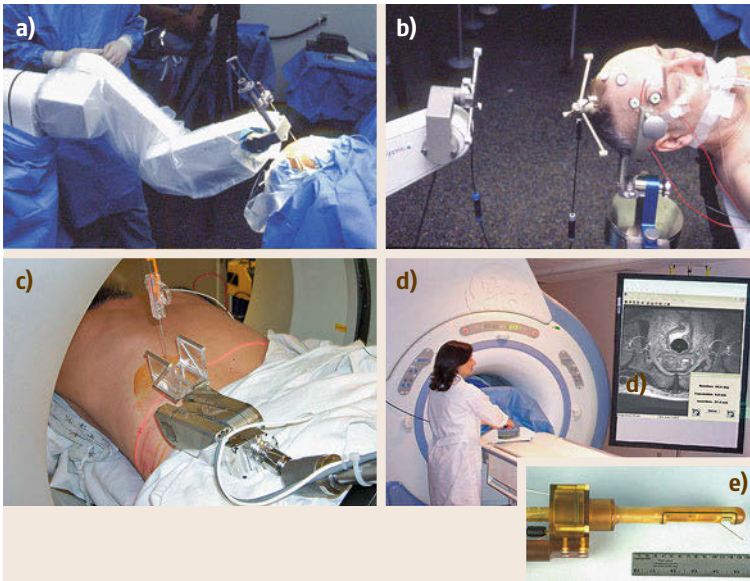


Fig.63.9a–e Clinically deployed systems for in-scanner needle placement. **(a,b)** The Neuromate system (after [63.19]) for stereotactic procedures in the brain uses a novel noncontact sensing system for robot-to-image registration; **(c)** Johns Hopkins system for in-CT needle placement (after [63.70, 71]); **(d,e)** Manually activated device for in-MRI transrectal needle placement into the prostate (after [63.72])

Freehand Needle Placement Systems

Freehand needle placement with **CT** and **MRI** guidance uses skin markers to locate the entry point [63.62], reference to the scanner's alignment laser to control needle direction, and markers on the needle to control depth. With ultrasound, the primary reliance is on surgeon experience or the use of some sort of needle guide to drive the needle to target while it passes in the ultrasound plane. Tracked ultrasound snapshots guidance combines orthogonal viewpoints with frozen ultrasound image frames [63.73]. Mechanical needle guides [63.61], hand-held navigation guidance [63.74], and optical guides have been combined with most imaging modalities. These include laser guidance devices [63.75], augmented reality systems [63.76]. Augmented reality with 2-D ultrasound [63.77] and **CT/MRI slices** [63.62] (Fig. 63.8b) was developed, where a semi-transparent mirror is used together with a flat-panel display to create the appearance of a virtual image floating inside the body in the correct position and size.

Passive and Semiautonomous Devices for Needle Placement

Passive, encoded manipulator arms were proposed for image-guided needle placement [63.78], where following a registration step, the position and orientation of a passive needle guide is tracked and the corresponding needle path is displayed on **CT** or **MRI** images. Semiautonomous systems allow remote, interactive image-guided placement of needles, such as transrectal prostate needle placement in **MRI** environment [63.72] with an actuated manipulator from outside

the scanner bore, while the needle driver is tracked in **MRI** with active coils.

Active Robots for Needle Placement

Neurosurgery was one of the first clinical applications of active robots [63.19, 20, 22], a natural application for surgical **CAD/CAM**. The entry and target points are planned on **CT/MRI** images, the robot coordinate system is registered to the image coordinate system (typically with markers affixed to the patient's head), and then the robot positions a needle or drill guide. The marker structure may be a conventional stereotactic head frame or, as in the Neuromate system [63.19], registration is achieved by simultaneous tracking of the robot and markers attached to the patient's skull. Spatial constraints in needle placement led to the development of structures achieving *remote center of motion* (**RCM**) or fulcrum motion [63.24, 25]. In these systems, the **RCM** is positioned at the entry point, typically with an active Cartesian stage or a passive adjustable arm, and the robot sets the needle direction and (sometimes) the depth. To speed up imaging, planning, registration, and execution, the robot can work concurrently with imaging devices, such as variants of an **RCM**-based system that was deployed with x-ray [63.24] and **CT** guidance [63.70, 71]. In [63.71], a marker structure was incorporated in the needle driver to register the robot with a single image slice. **MRI** has an excellent potential for guiding, monitoring, and controlling therapy, invoking intensive research on **MRI**-compatible robotic systems for needle placement [63.79] and other more interactive procedures [63.50]. Ultrasound guid-

ance offers many unique advantages: is relatively inexpensive and compact, provides real-time images, does not involve any ionizing radiation, and does not impose significant materials constraints on the robot design. Several robotic systems have been proposed for prostate interventions [63.80] using transrectal ultrasound guidance. For other ultrasound-guided needle placement applications, examples include experimental systems for liver [63.64, 81], gallbladder [63.82], and breast [63.83]. Figure 63.8d shows one example of the use of information overlay to assist in needle placement in a telesurgical application [63.64]. Whatever form of image feedback is available, steering flexible needles to hit desired targets while avoiding obstacles is a ubiquitous problem, having led to several novel approaches [63.84, 85] and reviewed most recently in [63.86]. Concentric tube robots (also interchangeably called *active cannulas* due to their usefulness in medicine), consist of several precurved elastic tubes nested within one another. Actuators grasp these tubes at their bases and extend them telescopically while also applying axial rotations. These movements cause the overall device to elongate and bend, providing a needle-sized device that moves in a manner analogous to a tentacle. Chronologically, a precursor to current concentric tube robots was an early steerable needle design where a curved stylet was used at the tip of a needle to induce steering [63.87]. These robots fall within the broader class of continuously flexible robots called *continuum robots* (see [63.15] for a review.) Over the past few years, mechanics-based models of active cannulas have rapidly matured due to the simultaneous parallel efforts of several research groups [63.14, 88]. Today, these models provide the basis for an active subfield of research on teleoperative control, surgery-specific design, and motion planning research. Surgical applications suggested for concentric tube robots and are in various stages of development, ranging from purely conceptual to animal studies, which will make the next several years exciting for translational clinical research.

63.3.4 Telesurgical Systems

The concepts of telemedicine, telesurgery, and telepresence in surgery date from the 1970s. Since then, the potential for telesurgical systems to facilitate effective interventions in remote or hostile environments such as the battlefield, space, or thinly populated areas has continued to be recognized [63.89], and there have been some spectacular demonstrations including a transatlantic cholecystectomy [63.51] in 2001, experiments in Italy [63.90] and Japan [63.91] as well as more nearly routine use in Canada [63.52]. The oper-

ational difficulties due to the intrinsic communication delay of long distance tele-surgery affect usability and safety and make the regular use of tele-surgery quite uncommon.

However, the primary uses of telesurgical systems have been with the surgeon and patient in the same operating room. Teleoperated robots have been used for over 15 years in MIS, both as auxiliary surgical support systems to hold endoscopes or retractors [63.23, 25, 92–94] and as *surgeon extender* systems to manipulate surgical instruments [63.3, 26]. There has also been recent work to develop telesurgical systems for use within imaging environments such as MRI [63.95].

A primary challenge for auxiliary support systems is to permit the surgeon to command the robot while his or her hands are otherwise occupied. Typical approaches have included conventional foot switches [63.23], instrument-mounted joysticks [63.25], voice control [63.10, 25], and computer vision [63.25, 96, 97].

A common goal in surgeon extender systems is to provide a measure of telepresence to the surgeon, specifically, to give the surgeon the sensation of performing open surgery from inside the patient. In early work, Green et al. [63.98] developed a successful prototype system for telesurgery combining remote manipulation, force feedback, stereoscopic imaging, ergonomic design, etc. Subsequently, several commercial telesurgical systems have been applied clinically for MIS. Of these, Intuitive Surgical's da Vinci [63.3] has been the most successful, with over 2500 systems deployed as of 2013. Experience with these systems has demonstrated that a high-dexterity wrist is often critical for surgeon acceptance. Although originally targeted at cardiac surgery, as well as more general interventions, the most successful clinical applications to date are radical prostatectomies, where significant improvements in outcomes have been reported [63.99], and hysterectomy, where the clinical benefits compared to conventional laparoscopy are still being studied [63.100].

One emerging area for research exploits the inherent ability of telesurgical systems to act as *flight data recorders* during surgical procedures. Several authors [63.101–104] have begun analyzing such data for such purposes as measuring surgical skill, learning surgical gestures and motions, and providing data for surgical simulators. Another emerging area for research [63.105] focuses on semi-automation of surgical gestures between the surgeon and the robot, often based on learned models. Other research [63.106–108] exploits augmented reality methods to enhance the information available to the surgeon during telesurgical procedures.

63.3.5 Microsurgery Systems

Although *microsurgery* is not a consistently defined term, it generally indicates procedures performed on very small, delicate structures, such as those found in the eye, brain, spinal cord, small blood vessels, nerves, or the like. Microsurgical procedures are commonly performed under direct or video visualization, using some form of magnification (e.g., microscope, surgical loupes, high-magnification endoscope). The surgeon typically has little or no tactile appreciation of the forces being exerted by the surgical instruments and physiological hand tremor can be a significant factor limiting surgical performance. Robotic systems can help overcome these human sensory-motor limitations, and efforts to develop specialized systems for applications such as ophthalmology [63.6, 109–115] and otology [63.116–118]. Several groups have also experimented with magnetic manipulation for these applications [63.113, 119]. There have been several efforts to compare microsurgical anastomosis procedures using laparoscopic telesurgical systems to conventional microsurgery. Schiff et al. [63.120] among others reported significant reductions in tremor with either robot and significantly improved technical quality and operative times compared to conventional microsurgery. As the number of da Vinci systems has proliferated, such applications are increasingly common [63.121]. A number of groups have implemented telesurgery systems specifically for microsurgery [63.13, 122–124] [63.95, 109]. These systems are in various stages of development, from laboratory prototype to preliminary clinical experimentation.

Not all microsurgical robots are teleoperated. For example, the cooperatively controlled JHU Steady Hand robots [63.4, 5] [63.6, 115] shown in Fig. 63.3 are being developed for retinal, head-and-neck, neurosurgery, and other microsurgical applications. A modified version of this system has also been used for microinjections into single mouse embryos [63.125].

There have also been efforts to develop completely hand-held instruments that actively cancel physiological tremor, for example, Riviere et al. [63.126–128] have developed an ophthalmic instrument using optical sensors to sense handle motion and adaptive filtering to estimate the tremulous component of instrument motion. A micromanipulator built into the instrument deflects the tip with an equal but opposite motion, compensating the tremor. Simple mechanical devices [63.129] for reducing tremor in specific tasks have also been developed.

An additional type of hand-held microsurgical and micro-therapeutic devices is reported in [63.130], which describes an active microendoscope for neuroen-

doscopy and therapy of the spinal cord able to safely navigate in the subarachnoid space and to avoid dangerous contact with the internal delicate structures thanks to a system based on hydrojets. Hydrojets come from the lateral surface of the catheter and, appropriately tuned and oriented, allow the tip of the endoscope to proceed without touching the spinal cord internal walls. The shared control system of the neuroendoscope, based on processing, segmentation, and analysis of the endoscopic images, assists the safe advancement of the tool in real time [63.131].

63.3.6 Endoluminal Robots

The term *endoluminal surgery* was first coined by Cuschieri et al. [63.132] as a major component of endoscopic surgery. Endoluminal procedures consist of bringing a set of advanced therapeutic and surgical tools to the area of interest by navigating in the lumina (i.e., the tube-like structures) of the human body, such as the gastrointestinal (GI) tract, the urinary tract, the circulatory system, etc. Currently, most endoluminal robots are designed for gastrointestinal applications, although there has been some initial work for other areas. There are several advantages (from a robotics research perspective) of working in the GI tract. The GI tract is not sterile and relatively large in diameter. Further it can be punctured intentionally to reach other abdominal cavities in NOTES approaches.

Traditionally, catheters and flexible endoscopes for endoluminal procedures have been inserted and manipulated manually from outside the body with the assistance of one or more visualization systems (e.g., direct endoscopic video, x-ray fluoroscopy, ultrasound). One major challenge is limited dexterity making it difficult to reach the desired target. Typically, flexible endoscopes have a bendable tip that can be steered by means of cable drives, and catheters may have only a fixed bend on a guide wire. There is also the inherent difficulty of *pushing a rope*, which some companies are trying to address by using external magnetic field (e.g., [63.133]). Once the target site is reached, these limitations become even more significant. Very simple instruments can be inserted through working channels or slid over guide wires, but dexterity is severely limited and there is no force feedback beyond what can be felt through the long, flexible instrument shaft.

These limitations have led a number of researchers to explore integration of more degrees of freedom in the catheter/endoscope body, as well as the design of intelligent tips with higher dexterity and sensing capabilities. Early work by Ikuta et al. led to the development of a five-segment, 13 mm-diameter sigmoidoscope using shape-memory alloy (SMA) actuators.

Subsequently, *Ikuta et al.* developed 3 mm-diameter active endovascular devices using hydraulic actuators incorporating a novel band pass valve fabricated using micro-stereolithographic techniques [63.29].

Several examples exist of instrumented catheter tips with force sensors [63.134] that allow the right branch of the circulatory systems to be found by estimating the force generated between the tip and the vessel walls. Basically, these sensorized endoluminal devices belong to the larger group of micro-electromechanical systems (MEMS)-instrumented surgical devices and the same sensing technologies can be also exploited for microsurgery. A survey article by *Rebello* [63.135] provides an excellent overview of sensorized catheters and other MEMS-based devices in endoluminal and microsurgical applications.

Another approach to endoluminal robots is represented by systems that move under their own power through the body, rather than being pushed. Early work on such systems is well summarized in [63.136]. In 1995 *Burdick et al.* developed an inchworm-like mechanism for use in the colon. This device combined a central extensor for propulsion and inflatable balloons for friction enhancement with the slippery colon tissue. A more advanced inchworm design for a semi-autonomous robotic colonoscope was developed by *Dario et al.* [63.33] (Fig. 63.10). This device consists of a central silicone elongator, two clamping systems based on suction and gentle mechanical grasping of the colon tissue, and a silicone steerable tip integrating a complementary metal-oxide-semiconductor (CMOS) camera and a light-emitting diode (LED)-based illumination system. Thanks to its intrinsic flexibility, the robotic colonoscope applies forces on colon tissues that are ten times lower than those produced by traditional colonoscopies. This system is now clinically tested [63.137], and similar devices combining flexibility and painless operation have been proposed by some companies [63.138, 139]. Although the application is not endoluminal, the HeartLander system of *Riviere et al.* [63.31] shown in Fig. 63.11a,b shares many of the characteristics of these systems. It uses an inchworm-like gait to traverse the surface of the heart and to perform simple operation. An instructive paper on the combination between flexibility and stiffness of endoscopic devices for allowing painless manoeuvrability and stable anchoring when performing surgical tasks has been recently published [63.140]. It presents a number of design criteria and solutions for transforming endoscopic devices from diagnostic tools to stable surgical platforms.

The natural evolution of GI endoscopic devices is represented by endoscopic capsules [63.141] which keep the promise to make endoscopy of the GI tract

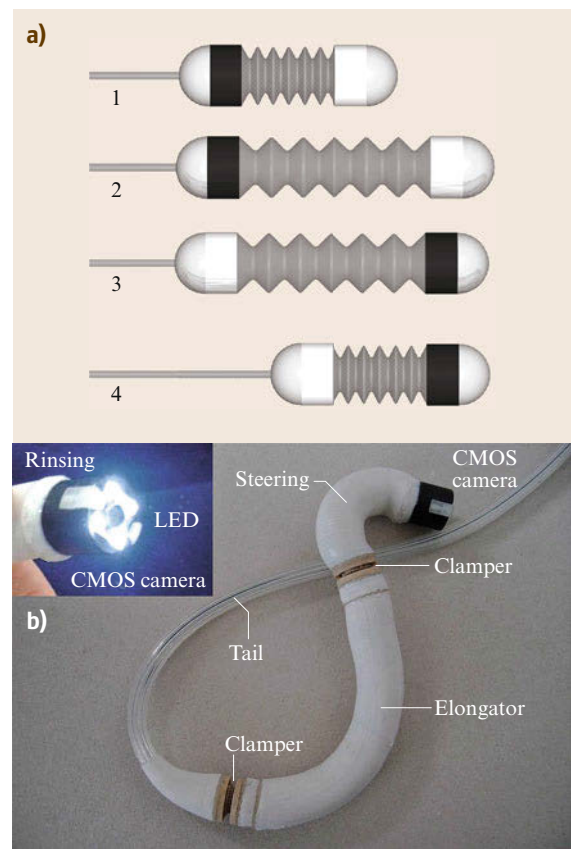


Fig.63.10a,b Medical robot for colonoscopy (after [63.33]): (a) the gait cycle of the robot, consisting of: (1) proximal clamping, (2) elongation, (3) distal clamping, and (4) retraction; (b) a recent working prototype used for clinical trials

a screening method highly tolerated by patients. For transforming simple CMOS swallowable cameras with illumination and transmission functionalities into useful diagnostic devices, several research groups have explored variegated solutions for active capsule locomotions. An example of legged locomotion capsules for GI application is illustrated in Fig. 63.11c and described in [63.28, 142]. In order to overcome dramatic powering problems, magnetic capsules propelled by permanent magnets [63.143] or by modified MRI fields [63.144] have been proposed. An earlier application of electromagnetic manipulation of an object within the body was the *video tumor fighter* of *Ritter et al.* [63.145].

63.3.7 Sensorized Instruments and Haptic Feedback

Surgical procedures almost always involve some form of physical interaction between surgical instruments

and patient anatomy, and surgeons are accustomed to use their haptic appreciation of tool-to-tissue interaction forces in performing surgical procedures. In situations such as where the clumsiness of instrumentation or human sensory-motor limitations limit the surgeon's ability to feel these forces, surgeons have been trained to rely on visual or other cues to compensate. Apart from the need for haptic feedback for diagnostic procedures and tissue identification, it has been demonstrated that reduced tactile and force information can result in the application of unnecessarily large forces on the patient during surgery, with possible harm to the patient [63.146]. The quality of haptic feedback available in currently deployed surgical robots is poor or nonexistent. Current research addresses the limitations firstly by integrating force and other sensors into surgical end-effectors and secondly by developing improved methods for processing and conveying the sensed information to the surgeon. However, the debate of the usefulness of force feedback in robot-assisted surgery is still open and is made more complex by the many scientific and technical difficulties due to the intrinsic presence of (possibly variable) communication time delay in the robotic system [63.147].

Although the most obvious way to *display* haptic information in a telesurgical system is directly through the master hand controllers, this method has several limitations, including friction and limited bandwidth in the hand controllers. Although these issues may be addressed through specialized design (which may raise costs and require other compromises) and improved control, there has been considerable interest in *sensory substitution* schemes [63.149–151] in which force or other sensor information is displayed visually, aurally, or by other means. Figure 63.8c shows one example of sensory substitution for warning when a da Vinci robot is about to break a suture [63.63].

Starting in the 1990s, several groups [63.151–153] have *sensorized* surgical instruments for microsurgery and MIS by equipping them with force sensors. Generally, these efforts relied on sensory substitution to display force data, either for freehand or telesurgical application. For example, *Poulose et al.* [63.152] demonstrated that a force sensing instrument used together with an IBM/JHU LARS robot [63.25] could significantly reduce both average retraction force and variability of retraction force during Nissen fundoplication. The first surgical robot with force feedback used in in vivo experiments was the JPL-NASA RAMS system, which was tested on animal models for vascular anastomosis [63.154] and carotid arteriotomies [63.155]. *Rosen et al.* [63.153] developed a force-controlled teleoperated endoscopic grasper equipped with position

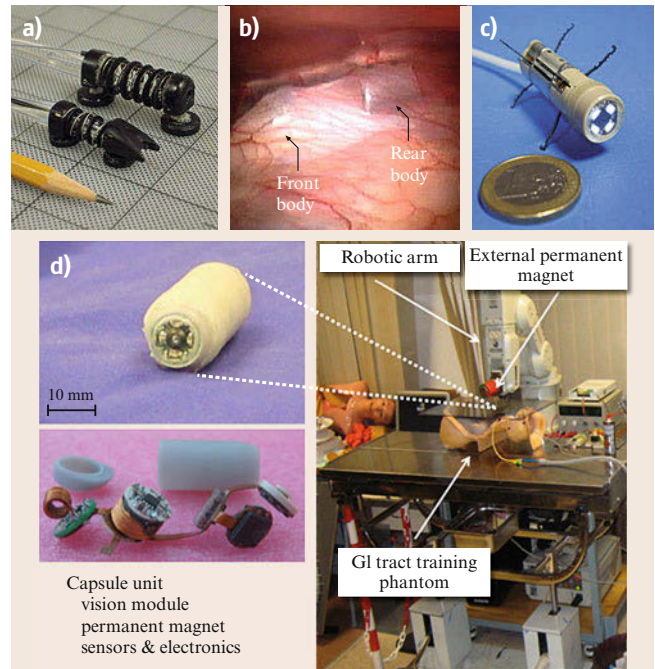


Fig.63.11a–d Mobility inside the body. **(a,b)** *HeartLander* device for crawling across the surface of the heart (after [63.31]). **(c)** Legged capsule for gastrointestinal diagnosis and therapy (after [63.28, 148]), **(d)** magnetic capsule for exploration of the GI tract, showing *left* capsule and components and *right* magnetic dragging platform based on a permanent magnet driven by a robotic manipulator (after [63.143])

sensors and actuated by direct-current (DC) motors whose output torque is sensed and fed back through motors integrated in a grasping handle. A similar approach was used by *Menciassi et al.* [63.156] for a microsurgery gripper equipped with semiconductor strain gauges and a PHANTOM (SensAble Technologies, Inc.) haptic interface. More recent work at Johns Hopkins has focused on incorporation of optical fiber force [63.157–160] and OCT [63.161–163] sensors into microsurgical tools. Both video and auditory sensory substitution [63.164], as well as direct feedback to robotic devices have been used to help surgeons control tool-tissue interaction forces and distance.

Several researchers [63.165] have focused on specialized *fingers* and display devices for palpation tasks requiring delicate tactile feedback (e.g., for detecting hidden blood vessels or cancerous tissues beneath normal tissues). There has also been work to integrate non-haptic sensors into surgical instruments, for example, *Fischer et al.* have developed instruments measuring both force and tissue oxygenation levels [63.166]. This information can be used for such purposes as assessing tissue viability, distinguishing between different tissue

types, and controlling retraction so as not to cause ischemic tissue damage.

Finally, it is important to note that sensorized surgical tools have important application beyond their direct use in surgical procedures, for example, one use is in biomechanical studies to measure organ and tissue mechanical properties to improve surgical simulators.

63.3.8 Surgical Simulators and Telerobotic Systems for Training

Medical education is undergoing significant changes. The traditional paradigm for surgical technical training is often summarized as *see one, do one, teach one*. This method can be effective in open surgery, where the surgical trainee directly observes the expert surgeon hands, sees the instrument motion, and follows the organ manipulation. However, in endoscopic surgery it is difficult to observe the surgeon's hand movements (outside the body) and the surgical tool actions (inside the body and only visible on a video monitor). In addition, endoscopic surgery requires different skills than open surgery, such as spatial orientation, interpretation of 2-D images in 3-D, and manipulating instruments through entry portals. These considerations led to introduction of surgical simulation systems of varying degrees of complexity and realism for endoscopic and other minimally invasive procedures. Nowadays, training simulators have achieved widespread acceptance in the field of anaesthesia, intensive care, flexible endoscopy, surgery, interventional radiology, and other fields. The use of simulators for training is so common that working groups have been set up in order to evaluate these training systems based on shared guidelines [63.167] and many teaching hospitals have extensive simulation training centers. Simulators are being validated on their basic parameters (face, content and construct) [63.168], whereas results on concurrent and predictive validity of simulation training are still not available.

Survey [63.169] divides training simulators into three groups, depending on the type of technology used: mechanical, hybrid, and virtual reality.

Mechanical simulators are boxes where objects or organs are placed and manipulated using surgical instruments. The manipulation is observed through a laparoscope and a screen. The simulated surgical task is observed by an experienced surgeon, who gives feedback to the trainee. Generally, there are no registration processes and the simulator must be reassembled after any training session. The *LapTrainer with SimuVision* (Simulab Inc., Seattle, USA) is a training system with a simulated laparoscope that consists of a boom-mounted digital camera in an open box trainer.

A hybrid simulator uses a box with objects or organs as a mechanical simulator, but in addition the performance of the trainee are monitored by a computer which gives guidance for the task execution and an objective feedback based on preplanned metrics. Thanks to this feedback, the assistance and judgement of an experienced surgeon are not strictly necessary, for example, the ProMIS (Haptica Inc., Boston, USA) is a typical hybrid simulator for training basic skills such as suturing and knot tying. Surgical instruments are passed through dedicated ports and the trainee receives the same haptic feedback as in real surgery during manipulation in the box. In addition, ProMIS analyzes the trainee's performance by tracking the instrument position in 3-D and by measuring the execution time, path length, and smoothness of task execution. Another recent hybrid simulator is the Perk Tutor open-source platform for ultrasound-guided percutaneous needle insertion training [63.170], which has been successfully applied in teaching of ultrasound-guided facet joint injections [63.171]. Specific to robotic surgery is the RoSS system [63.172], which simulates the operator console of the da Vinci robotic system. Intuitive Surgical currently markets the dv-Trainer [63.173] simulator for the da Vinci system, comprising the surgeon console from a da Vinci Si system and a computer back end to simulate the patient-side manipulators, and its efficacy is being evaluated [63.174].

Finally, *virtual-reality* training systems combine visualization and haptic interfaces to enable surgeons to interact efficiently and naturally with real-time computational models of patient anatomy [63.175]. The development of these systems is inherently a multidisciplinary effort, including real-time computer graphics, the development of high-bandwidth haptic devices, real-time biomechanical modeling of organs, tool-tissue interactions, expertise in training assessment, and human-machine information exchange, etc. [63.176]. Research in these areas is closely related to and synergistic with comparable developments in technology and systems for performing real interventions, for example, modeling of organ motion in response to forces is necessary to improve the accuracy of needle placement procedures. Haptic feedback devices must meet similar requirements whether the forces displayed are simulated or measured directly in telesurgery, and so on. Finally, as noted earlier, *sensorized* instruments and real-time imaging are critical sources of data needed to create realistic biomechanical models. The use of the computer graphical processor (GPU) allows the simulation of organs at rates in excess of 10 kHz [63.177], which enables good haptic feedback. Similarly, new physics-based graphical libraries support the development of low cost virtual reality simu-

lators that correct render the interaction of instruments and anatomical parts, and thus can support large training classes [63.178].

The variety of interface devices and virtual reality laparoscopic simulators is quite wide and increasing numbers of systems are becoming commercially available. The Phantom interface is used in conjunction with virtual simulators to provide users with realistic haptic feedback (SensAble Technologies Inc., Woburn, MA, USA). The Xitact LS500 laparoscopy simulator (Xitact S.A., Lausanne, Switzerland) is a modular virtual-reality simulation platform with software for training and assessing performance in laparoscopic tasks. It is an open system including all or some of these subsystems: laparoscopic tools, mechanical abdomen, a personal computer (PC) providing the virtual-reality scenario, a haptic interface, a force feedback system and a tracking system for the tools. Several other systems for virtual reality simulation exist that exploit the hardware from Xitact or Immersion Medical, Inc. (Gaithersburg, MD, USA) and that are dedicated to specific surgical tasks: Lapmentor [63.179], the Surgical Education platform [63.180], LapSim [63.181], Procedicus MIST [63.182], EndoTower [63.183], the Reachin laparoscopic trainer [63.184], Simendo [63.185], and the Vest system [63.186]. Specifically for training eye surgeons, the surgical simulator EYESi [63.187] uses advanced computer technology and virtual reality to simulate the feel of real eye surgery, making it possible for surgeons at all levels to acquire new skills and perfect their techniques in preparation for surgery on the human eye. Training for dexterity skills in robotic surgery is supported by the new virtual simulator *XRON* developed at the University of Verona, which interfaces physics-based simulation with several commercial joysticks and provides evaluation metrics of interactive tasks [63.188].

Making a comparison between these different categories of simulators is not trivial. Basically, box trainers and hybrid simulators require some experienced technicians for the set up and some organizational logistics due to legal and ethical factors related to the storage of freshly explanted organs. The most evident advantage of these simulators is that the tactile response from the manipulated objects is the same as in real surgery and complicated models of organs and tissue-tool interaction are not required. On the other hand, completely virtual-reality trainers are potentially very flexible, can take advantage of powerful graphical engines, but they are limited by the availability of realistic calibration data for the anatomical and biomechanical models. Although demonstrations exist of the ability of simulators to record, objectively score, and hone the psychomotor skills of novice surgeons [63.189], the debate about their value is still open because no multicentre trials has yet been conducted to determine their efficacy. Furthermore, it has been shown that simulation training must be included in structured curricula in robotic surgery, where trainees are also introduced to basic concepts of robotics and, in particular, to the so called *non technical* skills, e.g., organization, leadership and communication, which significantly affect the surgical outcome [63.190].

63.3.9 Other Applications and Research Areas

The research areas described above illustrate major themes within medical robotics, but they are by no means exhaustive. Many important application areas such as otolaryngology [63.191–194] and radiation therapy have necessarily been excluded for space reasons. For a fuller exploration, readers should consult the further reading suggestions in Sect. 63.4.

63.4 Conclusion and Future Directions

Medical robotics (and the larger field of *computer-integrated interventional medicine*) has great potential to revolutionize clinical practice by:

- Exploiting technology to transcend human limitations in treating patients
- Improving the safety, consistency, and overall quality of interventions
- Improving the efficiency and cost-effectiveness of robot-assisted patient care
- Improving training through the use of validated simulators, quantitative data capture and skill as-

essment methods, and the capture and playback of clinical cases

- Promoting more effective use of information at all levels, both in treating individual patients and in improving treatment processes.

From being the stuff of late-night comedy and science fiction 20 years ago, the field has reached a critical threshold, with clinically useful systems and commercial successes. The scope and number of research programs has grown exponentially in the past 8 years, and this chapter is by no means a comprehensive survey

of the field. In fact, such a survey would be practically impossible in less than 100 pages. Many important emerging systems and applications are necessarily left out. Interested readers are urged to refer to the further reading section for more complete treatments. In particular, the survey articles and books in listed at the end of this section collectively contain somewhat fuller bibliographies than space permits here.

In the future, we can expect to see continued research in all aspects of technology and system development, with increasing emphasis on clinical applications. As this work proceeds, it is important that researchers remember several basic principles. The first, and arguably most important, principle is that medical robotics is fundamentally a *team* activity, involving academic researchers, clinicians, and industry. Each of

these groups has unique expertise, and success comes from effective, highly interactive partnerships drawing upon this expertise. Building these teams takes a long-term commitment, and the successes in recent years are largely the pay-off from investments in creating these teams. Second, it is important to work on problems with well-defined clinical and technical goals, in which the criteria for measuring success are ultimately related to real advantages in treating patients. In working toward these goals, it is important to have measurable and meaningful milestones and to emphasize rapid iteration with clinician involvement at all stages. Finally, it is essential that all team members recognize the level of commitment that is required to achieve success and that they enjoy what they are doing.

Video-References

- VIDEO 823 Da Vinci Surgery on a grape
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/823>
- VIDEO 824 Da Vinci Xi introduction | Engadget
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/824>
- VIDEO 825 Intuitive surgical Da Vinci single port robotic system
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/825>
- VIDEO 826 SPORT system by Titan Medical
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/826>
- VIDEO 827 Robot for single port surgery by Nebraska University
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/827>
- VIDEO 828 Magnetic and needlescopic instruments for surgical procedures
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/828>
- VIDEO 829 CardioArm
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/829>
- VIDEO 830 Snake robot for surgery in tight spaces
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/830>
- VIDEO 831 IREP robot – Insertable robotic effectors in single port surgery
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/831>
- VIDEO 832 Variable stiffness manipulator based on layer jamming
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/832>
- VIDEO 833 Reconfigurable and modular robot for NOTES applications
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/833>
- VIDEO 834 SPRINT robot for single port surgery
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/834>
- VIDEO 835 A micro-robot operating inside eye
available from <http://handbookofrobotics.org/view-chapter/63/videodetails/835>

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64. Rehabilitation and Health Care Robotics

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The field of rehabilitation robotics considers robotic systems that 1) provide therapy for persons seeking to recover their physical, social, communication, or cognitive function, and/or that 2) assist persons who have a chronic disability to accomplish activities of daily living. This chapter will discuss these two main domains and provide descriptions of the major achievements of the field over its short history and chart out the challenges to come. Specifically, after providing background information on demographics (Sect. 64.1.2) and history (Sect. 64.1.3) of the field, Sect. 64.2 describes physical therapy and exercise training robots, and Sect. 64.3 describes robotic aids for people with disabilities. Section 64.4 then presents recent advances in smart prostheses and orthoses that are related to rehabilitation robotics. Finally, Sect. 64.5 provides an overview of recent work in diagnosis and monitoring for rehabilitation as well as other health-care issues. The reader is referred to Chap. 73 for cognitive rehabilitation robotics and to Chap. 65 for robotic smart home technologies, which are often considered assistive technologies for persons with disabilities. At the conclusion of the present chapter, the reader will be familiar with the history of rehabilitation robotics and its primary accomplishments, and will understand the challenges the field may face in the future as it seeks to improve health care and the well being of persons with disabilities.

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64.1 Overview

In this chapter, we discuss an application of robotics that will likely touch many of us in an acutely personal way at some point in our lives. When, through injury or disease, we become unable to interact physically with our immediate environment as we desire to achieve our personal goals, or when one of our family members, friends, or neighbors is in this situation, technology-based solutions will likely be a major component in the treatment interventions that therapists prescribe to assist us in re-learning how to complete our activities of daily living (ADL), or to assist us in actually doing them if we are unable to recover lost function. While human therapists and attendants can indeed shoulder the types of assistance required, the projected short-term demographics of many countries, including China, Japan, and the Scandinavian countries, show a growing shortage of working-age adults. Age-related disabilities will soon substantially impact the service sector job market, put many older and disabled people at risk, and increase the need for institutionalization when there is no viable home-based solution. National programs to develop personal robots, robotic therapy, smart prostheses, smart beds, smart homes, and tele-rehabilitation services have accelerated in the past 20 years and will need to continue apace with the ever increasing ability of health care to allow people to live longer through the repression of disease and improvement in surgical and medication interventions. Rehabilitation robotics, although only a 50 year old discipline [64.1–3], is projected to have a fast-growing future in the coming decades. Within the past 10 years, the field has seen significant strides in the commercialization of rehabilitation robotics due to an increasing acceptance of the validity of this approach by clinical care providers, as well as the cost reductions in sensors and actuators. We have also witnessed the expansion of applications from the social robotics research domain into rehabilitation, increasing the range of persons whose impairments can be targeted by robotic technologies in the years to come.

64.1.1 Taxonomy of Rehabilitation Robotics

The field of rehabilitation robotics is generally divided between the categories of *therapy* and *assistance* robots, although some devices can serve both purposes. In addition, rehabilitation robotics includes aspects of artificial limb (prosthetics) development, functional neural stimulation (FNS) and technology for diagnosis and monitoring of people during activities of daily living.

Therapy robots generally have at least two main users simultaneously, the person with a disability who is receiving the therapy and the therapist who sets up and monitors the interaction with the robot. As this type of therapy is moving into the home, a third user group has also become prominent: the disabled person's caregivers and family.

The Types of therapies that have benefited from robotic assistance are upper- and lower-extremity movement therapy, communication-enabling for children with autism and exploration-enabling (education) for children with cerebral palsy (CP) or other developmental disabilities (Chap. 73). A robot may be a good alternative to a physical or occupational therapist for the actual hands-on intervention for several reasons:

1. Once properly set up by a therapist – an essential role – an automated exercise machine can consistently apply therapy over long periods of time without tiring.
2. The robot's sensors can measure the work performed by the patient and quantify, to an extent not detectable by standard clinical scales, any recovery of function that may have occurred, which may be highly motivating for a person to continue in the therapy.
3. The robot may be able to engage the patient in types of therapy exercises that a therapist cannot do, such as computer game-based therapy or magnifying movement errors to provoke adaptation [64.4, 5].

One way to classify robotic solutions for application to rehabilitation therapy is by how they contact the patient [64.6].

Operational Therapy Robots (or End-Effector-Based Therapy Robots)

For these machines, the trajectories of the robot end-effector and that of the human end-effector, e.g., the hand or the foot, are physically coupled in operational space. In joint space, the trajectories of the robot joints and of the human joints can significantly differ. Main advantages of operational therapy robots are that: (a) they can be designed by using off-the-shelf components or robots; (b) they can be easily programmed in Cartesian space by nonexpert users. Main limitations are that: (a) they are not able to assist each single human joint independently; (b) patients using these robots are supposed to feature a minimum level of residual motor synergies in order to coordinate their own multijoint movement, producing the configurations of the affected limb required by the therapy exercise.

Wearable Therapy Robots (or Exoskeleton-Based Therapy Robots)

For these machines, a larger portion of the human body (typically the whole affected limb) is in continuous physical contact with the robot. In most cases, a biomimetic exoskeleton kinematic structure is selected. In this case, not only are the trajectories of the robot and human end-effectors the same in operational space, but the trajectories of the robot joints approximate those of the human joints in joint space. The main advantage of wearable therapy robots is the possibility of sensing the configuration and assisting each human joint independently. The main drawbacks of these systems are additional design considerations needed to avoid misalignments between robot and human joints, and to minimize the invasiveness for the patient in terms of weight, dimensions, and overall wearability (Sect. 64.2.4).

Non-Contact Therapy Robots (or Socially Assistive Robotics)

Robotic devices are also being developed for rehabilitation therapy that do not physically contact the patient, but instead monitor and coach the patient during therapy [64.7]. A key concept of this approach is that humans are wired to respond to embodied agents in ways that are important for motivation in rehabilitation therapy (see Chap. 73 for a detailed discussion of socially assistive robotics). One of the earliest robotic therapy devices, developed by Erlandson, can be classified as a socially assistive robot, as it provided reaching targets for patients rather than physically assisting movement [64.8] (see later). The main advantage of noncontact therapy robots is that of being intrinsically safe, since they are not supposed to physically interact with the patient, although this could limit significantly the scope of their clinical application.

From a design perspective, it is important to understand that therapy robots are tools typically intended for temporary use (i. e., the duration of the therapy at home or at the clinic), and are designed to maximize the objective clinical effectiveness of the therapy as well as the outcome and the efficiency of the entire clinical process.

Assistive robots, instead, are solutions for promoting independent living of disabled and elderly citizens. They need to be designed to be usable in a lifelong perspective in real-life scenarios, and thus, designers need to take into account (at a much more serious level than in the case of therapy robots) the end-user subjective preferences, and human factors, in general, in order to maximize their overall, long-term acceptability [64.6]. Whereas limited usability, some level of discomfort, or bad aesthetics might be tolerated by the patients expe-

riencing the application of a therapeutic tool used in a gym or at home, these same factors are unacceptable for disabled or elderly persons who are supposed to depend upon an assistive robot for activities of daily living in a variety of social contexts for the rest of their lives.

Assistive robots can be grouped on the basis of their focus on manipulation, mobility, or cognition. Manipulation aids can further be classified into fixed-platform and portable-platform and mobile-autonomous types. Fixed-platform robots perform functions in the kitchen, on the desktop, or by the bed. Portable types are manipulator arms attached to an electric wheelchair to hold and move objects and to interact with other devices and equipment, as in opening a door. Mobile-autonomous robots can be controlled by voice or other means to do manipulation and other errands in the home or workplace. Mobility aids are divided into electric wheelchairs with navigation systems and mobile robots that act as smart, motorized walkers, allowing people with mobility impairment to lean on them for fall-prevention and stability. The third main type, cognitive aids, assists people who have dementia, autism, or other disorders that affect communication and physical well-being.

The fields of prosthetics, orthotics, and functional electrical stimulation (FES) are closely allied with rehabilitation robotics. Prostheses are artificial hands, arms, legs and feet that are worn by the user to replace amputated limbs. Prostheses are increasingly incorporating robotic features [64.9, 10]. Robotic orthoses are actuated braces that can assist a person in walking or moving the arms or hands. FES systems seek to reanimate limb movements of people who are weak or paralyzed by electrically stimulating nerve and muscle. FES control systems are analogous to robotic control systems, except that the actuators being controlled are human muscles. Another related field is technology for monitoring and diagnosing health care issues as a person performs activities of daily living.

This chapter is organized according to this taxonomy. After providing background information on demographics (Sect. 64.1.2) and history (Sect. 64.1.3) of the field, Sect. 64.2 describes rehabilitation therapy and training robots, and Sect. 64.3 describes robotic aids for people with disabilities. Section 64.4 then reviews recent advances in smart prostheses and orthoses that are related to rehabilitation robotics. Finally, Sect. 64.5 provides an overview of recent work in diagnosis and monitoring for rehabilitation as well as other health-care issues.

64.1.2 World Demographics

Different areas of rehabilitation robotics focus on different user populations, but a linking characteristic

of these populations is that they have a disability. Disability is defined in the US with the Disabilities Act as *A physical or mental impairment that substantially limits one or more of the major life activities*. Worldwide disability, based on survey results from the WHO ranges from about 10 to 40% of the population, depending on gender, age, wealth, and residence, with an overall prevalence of about 16% (Table 64.1). Prevalence is the proportion of a population who have (or had) a specific characteristic in a given time period. In medicine, typically this characteristic is an illness or impairment. Prevalence is usually expressed as a percentage (e.g., 5%), or as the number of cases per 10 000 or 100 000 people, depending on how common the illness or risk factor is in the population. Across all other parameters, there is approximately a 4 : 1 disparity in disability rates in the elderly population (>60 years) over working-class adults. In addition, lower birth rates and life-extending health care are the dominant factors contributing to the aging of the population and concomitant rise in disability overall. Other factors, such as China’s population control policies of the 1970s, have created a lack of working-age adults to support the world economy. These and other factors make it clear that rehabilitation robotics developers will be faced with users who, as a demographic group, have generally lower levels of sensory and motor capability, and may have impaired cognition as well. The urgency of making advances in this field is increasing in line with the demographics.

64.1.3 Short History of Rehabilitation Robotics

The history of rehabilitation robotics is almost as old as that of robotics itself, although emanating from very different sources. Several book chapters and papers have been written on the history of rehabilitation

robotics in more detail than this section [64.1, 19, 20], and numerous papers in the proceedings of the IEEE International Conference on Rehabilitation Robotics also provide more grounding for historical perspective. The chronology below pays particular attention to early work and to projects with notable clinical and/or commercial impact.

Early robotics, starting in the late 1950s, focused on large manipulators to replace workers in factories for dirty, dangerous, and undesirable tasks. The earliest rehabilitation robots came from the field of prosthetics and orthotics (P&O). Both the Case Western University Arm (1960s) and the Rancho Los Amigos *Golden Arm* (early 1970s) (reviewed in [64.19]) were adaptations of replacement mechanical arms meant as powered orthoses [64.1]. The user drove the *Golden Arm* with a set of tongue-operated switches, joint-by-joint, an arduous means of endpoint control. In the mid-1970s, the Department of Veterans Affairs began funding a group at the Applied Physics Lab under the guidance of *Seamone* and *Schmeisser* to computerize an orthosis mounted on a workstation to perform activities of daily living (ADL) tasks such as feeding a person and turning pages [64.21]. For the first time, a rehabilitation robot had a command-type interface, not just a joint-by-joint motion controller.

The 1970s also saw the French *Spartacus* system being developed, guided by the vision of *Vertut*, for use by people with high-level spinal cord injury (SCI) as well as children with CP [64.22]. This system did not emerge from the P&O field but was developed by the French Atomic Energy Commission (CEA), which used large tele-manipulators for nuclear fuel rod handling. One of these was adapted so that people with movement impairment could control it using a joystick for pick-and-place tasks. A decade later, one of the researchers on the *Spartacus* project, *Kwee*, began the Dutch MANUS Project [64.23] a dedicated effort to develop the first wheelchair-mounted manipulator de-

Table 64.1 Prevalence of disability and aging in selected countries (after [64.18])

Country	Number people with disabilities	Percentage of population with disabilities	Number of elderly people	Percentage of population that is elderly
France	5 146 000	8.3	12 151 000	19.6
USA	52 591 000	20.0	35 000 000	12.4
Great Britain	4 453 000	7.3	12 200 000	29.5
Netherlands	1 432 000	9.5	2 118 808	13.4
Spain	3 528 220	8.9	6 936 000	17.6
Japan	5 136 000	4.3	44 982 000	35.7
Korea	3 195 000	7.1	16 300 000	36.0
Italy	2 609 000	4.8 [64.11]	12 302 000	20.3 [64.12]
Germany	7 101 682	8.7	16 844 300	21.0 [64.13]
China	84 600 000	6.5 [64.14]	122 880 000	9.1 [64.15]
India	21 000 000	1.8 [64.16]	67 117 826	5.6 [64.17]

signed expressly as a rehabilitation robot, not adapted from a design from another field.

In between, several other major programs were begun. In 1978, at Stanford University, and then with decades-long funding from the US Department of Veterans Affairs, Leifer started the Vocational Assistant Robot program, culminating in several clinically tested versions of the Desktop robot, DeVAR [64.3, 24, 25], the mobile version, MoVAR [64.26], and finally a Professional version, ProVAR, developed by Van der Loos et al., which had the advanced ability for the user to program tasks in an easy-to-use browser-type environment [64.27]. Although DeVAR briefly made it onto the market in the early 1990s, multisite user testing revealed this industrial-arm-based approach to assistive robotics was still too costly for the low level of functionality achieved, even with ProVAR's advanced interface.

In the mid-1980s, from observations on the unsuitability of existing industrial, educational and orthosis-derived manipulators for rehabilitation applications, Tim Jones at Universal Machine Intelligence (later Oxford Intelligent Machines: OxIM) in the UK began an intensive effort to provide the rehabilitation robotics community with its first workhorse system especially designed from the ground up for human service tasks. Over 10 years, a series of systems, starting with the RTX model, were used in numerous research labs and clinics around the world. The most extensive effort to use the OxIM arm was in France, and a suite of research projects, funded by the French government and the European Research Commission, starting as RAID, then as MASTER [64.28], developed and clinically tested workstation-based assistive systems based on the RTX and subsequent OxIM arms. When OxIM ceased building its arms, the French company Afma Robotics [64.29] took over efforts to commercialize the MASTER system, although it has also stopped production.

The UK witnessed the first commercially available feeding robot, Handy-I, an inexpensive and well-received device first designed by Topping and then commercialized by Rehabilitation Robotics, Ltd. in the 1990s [64.30]. Primarily for people with CP to achieve a measure of independence in feeding themselves, task environments later also included face washing and applying cosmetics, areas of high demand identified by its users.

The history of mobile manipulator applications began in the 1980s with adaptations of educational and industrial robots, and achieved a boost with the funding of the US National Institute on Disability and Rehabilitation Research (NIDRR) for a Rehabilitation Engineering Research Center on Rehabilitation Robotics

(RERC) at the AI duPont Hospital in Delaware from 1993 to 1997. With its ability to fund dozens of research projects in parallel, it also formed a partnership with a local company, Applied Resources, Corp. (ARC), which developed and marketed several rehabilitation technology products. One of the RERC researchers, Mahoney, moved to ARC and was instrumental in extending the company's repertoire to the RAPTOR wheelchair-mounted arm [64.31].

In Europe, the most significant mobile manipulator project was the MANUS Project [64.23] mentioned earlier. With much of the work done under the direction of Kwee at the iRV (Rehabilitation R&D Center) in the Netherlands, the project culminated in a robot specifically designed for wheelchair mounting, with user control through a joystick and feedback by a small display on the arm itself. This project led to numerous follow-on research projects, and, most significantly, to the commercialization of the system by Exact Dynamics, BV, in the Netherlands. The company's current product, called the iARM, is provided on physician prescription by the Dutch Government to qualified people with a disability, such as CP or tetraplegia from an SCI.

Realizing a potential growth in this market niche, the Canadian company, Kinova Robotics, in 2009 began commercializing a competing product, called the Jaco Arm [64.32], with a different design approach. Using carbon fiber segments and lightweight actuator and control components, the payload specifications and control options are approximately the same as for the iARM, but achieved at a lower arm weight.

Autonomous navigation systems on electric wheelchairs began in the 1980s also, benefiting initially from the development by Polaroid Corp. of range finders for its cameras using ultrasonic sensors. They were inexpensive, and small enough, at 30 mm in diameter, that dozens of them could be placed around the periphery of a wheelchair to aid medium-range navigation (≈ 10 –500 cm). In the 1990s and early 2000s, with the advent of vision-based servoing and laser-range scanners, algorithms for faster, smarter, less-error prone navigation and obstacle avoidance dominated research advances in this sector. In Korea, for example, Bien et al., at the KAIST Human Welfare Robotics Center began developing the KARES line of wheelchair-based navigation systems in the late 1990s [64.33] and the NavChair project at the University of Michigan was the start of a development line that led to the commercialized Hephaestus system at the University of Pittsburgh [64.34, 35].

Therapy robots had a later start than assistive robots. Research on upper extremity therapy robots started in the mid-1980s with early exercise devices, such as the BioDex [64.36] a first step in programmable,

force-controlled, albeit single-axis devices. The first multi-axis concept was published by *Khalili and Zomlefer* [64.37], and the first tested system by *Erlandson et al.* at Wayne State University emerged in the mid-1980s as well [64.8]. The RTX manipulator had a touch-sensitive pad as an end-effector, presenting targets at different locations for patients with upper extremity weakness (e.g., following a stroke) to hit after the screen gave a visual signal. Software logged response times, thereby providing a score that was tallied and compared to previous sessions. Later robots used advanced force-based control, which required significantly more computer power. The early-1990s saw the start of the MIT-MANUS Project with Hogan and Krebs, simple robotic devices designed for bimanual therapy after stroke designed by *Lum et al.* at U.C. Berkeley [64.38, 39], followed a few years later by the Palo Alto VA MIME (mirror image motion enabler) Project [64.40] and its derivative, Driver's SEAT [64.41], with Bugar, Van der Loos and Lum, as well as the Rehabilitation Institute of Chicago ARM Guide Project with *Reinkensmeyer et al.* [64.42]. Each had a different philosophy on upper extremity stroke therapy and each was able to demonstrate clinical effectiveness in a different way. Several of these programs, now two decades later, have made significant technical advances, and all the investigators are still active in the field. Current work is described in subsequent sections of this chapter.

Research on lower extremity therapy robots began with the work of Scherb in 1919 who proposed an approach called *mechanotherapy* [64.43]. He also developed a prototype, depicted in Fig. 64.1, of a cable-driven machine for assisting the motion of the lower limbs for bedridden patients. In 1976, the use of a master/slave exoskeleton system for lower limb therapy was introduced by the French physicians *Bel and Rabischong* [64.44], who developed

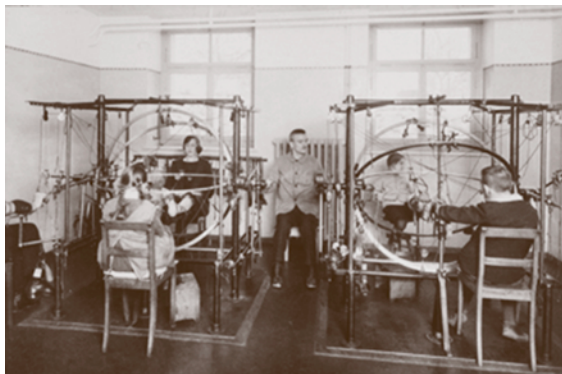


Fig. 64.1 The meridian. A universal machine for applying passive motion to any joint (after [64.43])

a pneumatically actuated wearable robot to be used for assisted therapy of paraplegic patients (Fig. 64.2). The robot movements were remotely controlled by a therapist who wore a master device capable of sensing and recording the configuration of her/his lower limbs.

About 20 years later, the Lokomat project for the development of a stand-alone, programmable wearable robot for lower extremity was launched and originated the establishment of the Hocoma company by Colombo and Hostettler. The first prototype of the Lokomat system [64.45] was developed in close cooperation with the Balgrist University Hospital in Zurich and initially applied to patients who had had spinal cord injuries (Fig. 64.3b). During the same time, *Hesse and Uhlenbroch* developed the Gait Trainer [64.46], (Fig. 64.3a), which allowed training without the use of a treadmill by controlling the center of mass (COM) in both in the vertical and horizontal directions.

In the last decade the growth in rehabilitation robotics has been characterized by the development of new devices (as explained above) as well as by new investigation methods aimed at understanding brain changes induced by rehabilitation. A recent clinical study [64.50] confirms that high-intensity, repetitive, and task-oriented training yields a faster learning and recovery time. Robots are also a key-enabling technology for labor-intensive and patient-tailored training as well as for accurately imposing spatial and temporal constraints within interactive scenarios so as to augment patient involvement [64.51]. A recent international online survey, distributed through professional organizations to therapists, has set out a set of important robotic rehabilitation device requirements [64.52], such as variety of arm movements, biofeedback to patients, adjustable resistance, and need for virtual activities. Robots offer the advantage of providing ob-



Fig. 64.2 This machine developed by Professor Rabischong allows the patient in rehabilitation to maintain her balance while inciting her muscles to move (after [64.47])



Fig. 64.3a–e Gait-training robotic systems in use in clinics; **(a)** the gait trainer GT-I, developed by Hesse's group and commercialized by Reha-Stim (Germany), **(b)** the Lokomat, developed by Colombo and colleagues and commercialized by Hocoma AG (Switzerland), **(c)** AutoAmbulator, developed by the HealthSouth Corp. (USA), **(d)** LokoStation with Lokohelp (Darkov Spa, Czech Republic; after [64.48]), **(e)** G-EO Evolution (Panos Th. Skoutas S.A., Greece; after [64.49])

jective measures of user performance, thus enabling the development of quantitative kinematic and dynamic metrics [64.53–56]. The analysis of brain reorganization and associated clinical outcomes induced by robot-aided therapy in chronic stroke patients have shown that motor performance improvement is correlated with changes in inter-hemispheric connectivity between primary somatosensory areas: for those patients the connectivity returns to nearly *physiological levels* [64.57].

Protocols based on monitoring patient performance, strength, endurance, and emotional state are being investigated. Anticipating patient movement intentions and modeling internal states lead to adaptive patient–

robot interaction control. This approach paves the way to a new generation of robotic therapy devices using *bio-cooperative* controllers, where *psychophysiological* and biomechanical information is used as feedback for updating robot control [64.58–60]. First examples of biocooperative controllers can be found in the robotic platforms developed within the European projects ECHORD/MAAT [64.56] (multimodal interfaces to improve therapeutic outcomes in robot-assisted rehabilitation) (Fig. 64.4) and *MIMICS* (multimodal immersive motion rehabilitation with interactive cognitive systems). Other bio-cooperative controllers have been developed by *Riener* and *Munih* [64.58], who developed new control strategies applied to lower limb

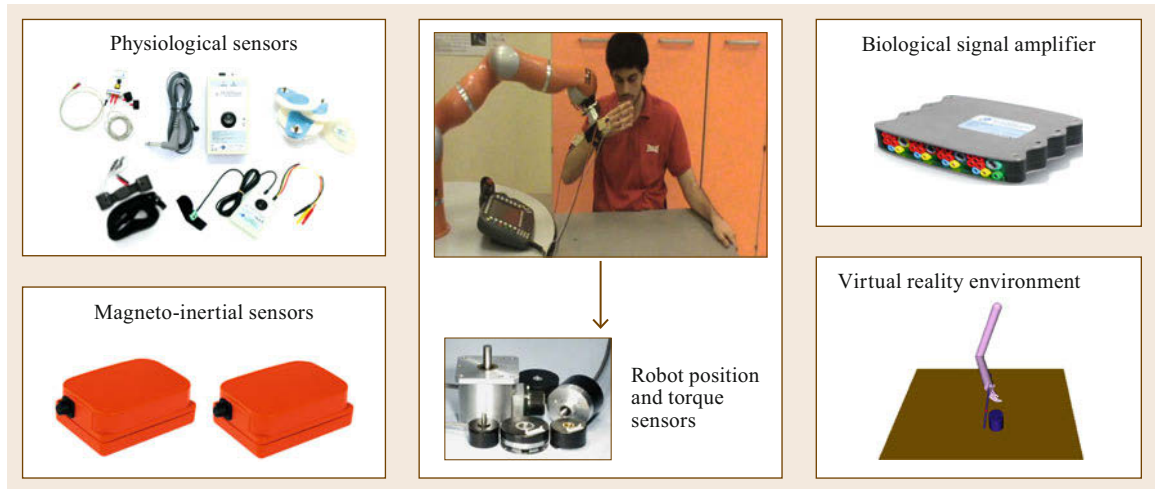


Fig. 64.4 Set up of the MAAT platform (after [64.61])



Fig. 64.5 PARO, an advanced interactive robot developed by AIST (after [64.62])

rehabilitation protocols that promote active participation of patients during training.

Cognitive robotics had started in the early 1980s to aid children with communication disorders and physical impairment to achieve a measure of control of their physical space. Using mostly educational manipulators, several demonstration systems were developed.

In the early 2000s, Latham of Anthrotronix, Inc. commercialized small robot systems to enable children with physical disabilities to play games with simple interfaces. A bit later, small mobile robots were used in clinics by *Dautenhahn* and *Werry* [64.63] with children who had autism, since robots have such simple interfaces that they appear not to be that challenging as communication with other humans. The early 2000s also saw the advent of pet robots, such as the Paro seal robot developed by *Shibata* et al. [64.64] (Fig. 64.5), as companions for both children and the elderly who are confined to clinics and have limited real companionship. This topic is further elaborated in Chap. 73.

The applications for robotics continues to increase in number as advances in materials, control software, higher robustness, and the diminishing size of sensors and actuators allow designers to attempt new ways of using mechatronics technology to further the well-being of people with disabilities.

64.2 Rehabilitation Therapy and Training Robots

The human neuromuscular system exhibits use-dependent plasticity, which is to say that use alters the properties of muscles and neurons, including the pattern of their connectivity, and thus their function [64.65–67]. For a detailed description of patient populations expected to benefit from robot-assisted therapy and the most common impairments to be treated, which include incoordination, abnormal synergies, spasticity and weakness, please see [64.50, 68–70].

64.2.1 Grand Challenges and Roadblocks

The process of neurorehabilitation seeks to exploit use-dependent plasticity in order to help people to relearn how to move following neuromuscular injuries or diseases. Neurorehabilitation is typically provided by skilled therapists, including physical, occupational, and speech therapists. This process is time-consuming, involving daily, intensive movement practice over many

weeks. It is also labor-intensive, requiring hands-on assistance from therapists. For some tasks, such as teaching a person with poor balance and weak legs to walk, this hands-on assistance requires that the therapists have substantial strength and agility to provide safe and effective interventions.

Because neurorehabilitation is time and labor intensive, in recent years healthcare players have put limits on the amount of therapy that they will reimburse in an effort to contain spiraling healthcare costs. Ironically, at the same time, there has been increasing scientific evidence that more therapy can in many cases increase movement recovery via use-dependent plasticity [64.71]. As robotics and rehabilitation researchers began to recognize beginning in the late 1980s, neurorehabilitation is a logical target for automation because of its labor-intensive, mechanical nature, and because the amount of recovery is linked with the amount of repetition. Robots could deliver at least the repetitive parts of movement therapy at lower cost than human therapists, allowing patients to receive more therapy, recover more function, remain independent longer, and reduce downstream healthcare expenses.

The grand challenge for automating movement therapy is determining how to optimize use-dependent plasticity. That is, researchers in this field must determine what the robot should do in cooperation with the patient's own movement attempts in order to maximally improve movement ability, all the while engaging the patient. Meeting this challenge involves solving two key problems: determining appropriate movement tasks (what movements should patients practice and what feedback should they receive about their performance), and determining an appropriate pattern of mechanical input to the patient during these movement tasks (in other words, at what magnitude, how often, and in which directions, should the robot apply forces to the patient's limb to provoke increased plasticity). The prescription of movement tasks and mechanical input fundamentally constrains the mechanical and control design of the robotic therapy device.

There are three main roadblocks to achieving the grand challenge. The first is a scientific roadblock: neither the optimal movement tasks nor the optimal mechanical inputs are known. The scientific basis for neurorehabilitation remains ill-defined, with competing schools of thought. The number of large, randomized, controlled trials that have rigorously compared different therapy techniques is still small, in part because these trials are expensive and difficult to control well. Therefore, the first problem that a robotics engineer will encounter when setting out to build a robotic therapy device is that there is still substantial uncertainty as to what exactly the device should do.

This uncertainty corresponds to an opportunity to use robotic therapy devices as scientific tools themselves. Robotic therapy devices have the potential to help identify what exactly provokes plasticity during movement rehabilitation, because they can provide well-controlled patterns of therapy. They can also simultaneously measure the results of that therapy. Better control over therapy delivery and improved quantitative assessment of patient improvement are two desirable features for clinical trials that have often been lacking in the past. Recent work with robotic movement training devices is leading, for example, to the characterization of computations that underlie motor adaptation, and then to strategies for enhancing adaptation based on optimization approaches [64.5, 72, 73]. Early work at UBC on the characterization of human balance in quiet standing will lead to the ability to use robotics clinically to develop new therapies to prevent falls for stroke survivors and others with balance impairment [64.74, 75].

The second roadblock is a technological one: robotic therapy devices often have as their goal to assist in therapy of many-body degrees of freedom (e.g., the arms and torso for reaching, or the pelvis and legs for walking). The devices also require a wide dynamic bandwidth such that they can, for example, impose a desired movement on a patient who is paralyzed, but also *fade-to-nothing* as the patient recovers. Further, making the devices lightweight enough to be wearable is desirable, so that the patient can participate in rehabilitation in a natural setting (for example, by walking over ground or working at a counter in a kitchen), or even throughout the course of normal activities of daily living. The development of high degree-of-freedom, wearable, high-bandwidth robotic exoskeletons is an unsolved problem in robotics, although much progress has been made toward this goal in the last 10 years, as described below. Still, no device at present comes close to matching the flexibility of a human therapist, in terms of assisting in moving different body degrees of freedom in a variety of settings (e.g., walking, reaching, grasping, neck movement), or the intelligence of a human therapist, in terms of providing different forms of mechanical input (e.g., stretching, assisting, resisting, perturbing) based on a real-time assessment of the patient's response.

The third roadblock is maintaining the motivation and engagement of the patient through the tens of thousands of repetitions required to achieve meaningful increases in function [64.50] that will carry over to performing actual ADLs. Rehabilitation can be compared to the exercise required by an athlete to compete at an elite competition level. By necessity, therapy at this intensity will have to move largely to the home setting to be economically viable, and therefore motivation

becomes the key ingredient of success. Current work focuses on developing adaptive therapy through robotics and feedback, embedding therapy in computer games, music, and sport, and applying motor-learning theories, for example, the *Challenge Point* [64.76] model of keeping people at a desirable difficulty level, to maximize effectiveness and minimize frustration over the long term [64.76]. Meeting the grand challenge of robotic therapy therefore will require substantial, inter-related advances in clinical neuroscience, robot engineering, and kinesiology.

64.2.2 Movement Therapy After Neurologic Injury

Modern, evidence-based medicine relies on objective evaluation and quantitative comparative analysis of the impact of different therapeutic approaches. Robotics technology has the potential to boost evidence-based neurorehabilitation: therapy robots provide precise and sensitive tools for assessing and modeling human behavior, well beyond the capability of a human observer. This is of paramount importance for enabling appropriate initial diagnosis, early adoption of corrective clinical strategies, and for identifying verifiable milestones as well as prognostic indicators of the recovery process.

Bosecker et al. [64.77] tried to evaluate clinical scores during upper limb therapy by means of robot-based metrics; *Zollo et al.* [64.54, 78] evaluated robotic therapy exploiting robotic outcome; thus providing quantitative measure of biomechanical and motion planning features of arm motor control following upper limb rehabilitation. A recent study carried out by *Krebs et al.* showed that robotic measurements of arm movements after upper limb, robot-aided therapy may establish biomarkers for motor recovery [64.79]. Similarly, *Domingo and Lam* [64.80] tried to apply robot-based assessment to the lower limb by using the Lokomat system and customized software.

Another important advantage of therapy robots is the possibility that a single operator can effectively supervise multiple patients, locally or even remotely, i. e., in a telerehabilitation scenario [64.81]. Therapy robots can potentially improve patients' access to rehabilitation by providing the opportunity to increase the duration and the frequency of their therapy experience, with limitations mainly depending on clinical considerations rather than on other organizational or economic constraints.

At present, much of the activity in physical therapy and training robots has been focused on retraining movement ability for individuals who have had a stroke or **SCI**, or are affected by **CP**. The main reasons

for this emphasis are that there are a relatively large number of patients with these conditions, the rehabilitation costs associated with them are high, and because these patients can sometimes experience large gains with intensive rehabilitation because of use-dependent plasticity.

A stroke refers to an obstruction or breakage of a blood vessel supplying oxygen and nutrients to the brain. Approximately 800 000 people suffer a stroke each year in the United States, and about 80% of these people experience acute movement deficits [64.82]. In Europe, 1 100 000 people suffered a stroke in 2000, and they are expected to increase up to 1 500 000 in 2025. There are over 3 000 000 survivors of stroke in the United States [64.83], with over half of these individuals experiencing persistent, disabling, movement impairments. Data are similar to those of Europe, where it has been estimated that between half and two-thirds of people survive stroke. Of these, half do not recover fully, and a quarter need assistance in daily living. While most of the survivors of stroke are elderly persons, motor impairment from a stroke affects 3000 of the 10 000 children born with **CP** each year [64.83]. While this is a small proportion of all stroke survivors, the motor function impairment will persist throughout the person's entire life, so the impact on independence is disproportionately large.

The number of people who have experienced and survived a stroke is expected to increase substantially in the United States and other industrialized countries in the next two decades, mostly because age is a risk factor for stroke and the mean age of people in industrialized countries is rapidly increasing due to the baby boom of the 1950s, but also because improved acute treatments will allow more people to survive a stroke, albeit perhaps with impairment.

The number of people who experience an **SCI** in the United States each year is relatively smaller – about 15 000, with about 200 000 people alive who have survived an **SCI** – but the consequences can be even more costly than stroke [64.82]. In Europe, there are about 11 000 new cases of **SCI** per year, and about 330 000 have survived an **SCI** [64.84]. The most common causes of **SCI** are automobile accidents and falls. These accidents crush the spinal column and contuse the spinal cord, damaging, or destroying neurons within the spinal cord. Lower limb robotic therapy has demonstrated promising results when applied to **SCI** patients with incomplete lesions [64.85] although large, systematic, and randomized controlled trials are still missing. It is important to note that **SCI** patients are typically younger than stroke patients, which may affect their familiarity with and acceptance of technical aids.

64.2.3 Robotic Therapy for the Upper Extremity

This section first describes early, clinically tested upper limb therapy robot systems (Fig. 64.6a–e), then more recent systems.

MIT-MANUS

The first robotic therapy device to undergo extensive clinical testing, and, now, to achieve some commercial success, is the MIT-MANUS, sold as the InMotion2 by Interactive Motion, Inc. [64.86]. MIT-MANUS is a planar two-joint arm that makes use of the SCARA configuration, allowing two large, mechanically grounded motors to drive a lightweight linkage. The patient sits across from the device, with the weaker hand attached to the end-effector, and the arm supported on a table with a low-friction support. By virtue of the use of the SCARA configuration, the MIT-MANUS is perhaps the simplest possible mechanical design that allows planar movements while also allowing a large range of forces

to be applied to the arm without requiring force feedback control.

MIT-MANUS assists the patient in moving the arm across the table-top as the patient plays simple video games, such as moving a cursor into a target that changes locations on a computer screen. Assistance is achieved using a position controller with an adjustable impedance. Additional modules have been developed for the device for allowing vertical motion [64.87], wrist motion [64.88], and hand grasp [64.89]. Software has been developed for providing graded resistance as well as assistance to movement [64.90], and for varying the firmness and timing of assistance based on real-time measurements of the patient's performance on the video games [64.91].

MIT-MANUS has undergone extensive clinical testing in several studies, summarized as follows. The first clinical test of the device compared the motor recovery of acute stroke patients who received an additional dose of robot therapy on top of their conventional therapy, to that of a control group, who received con-

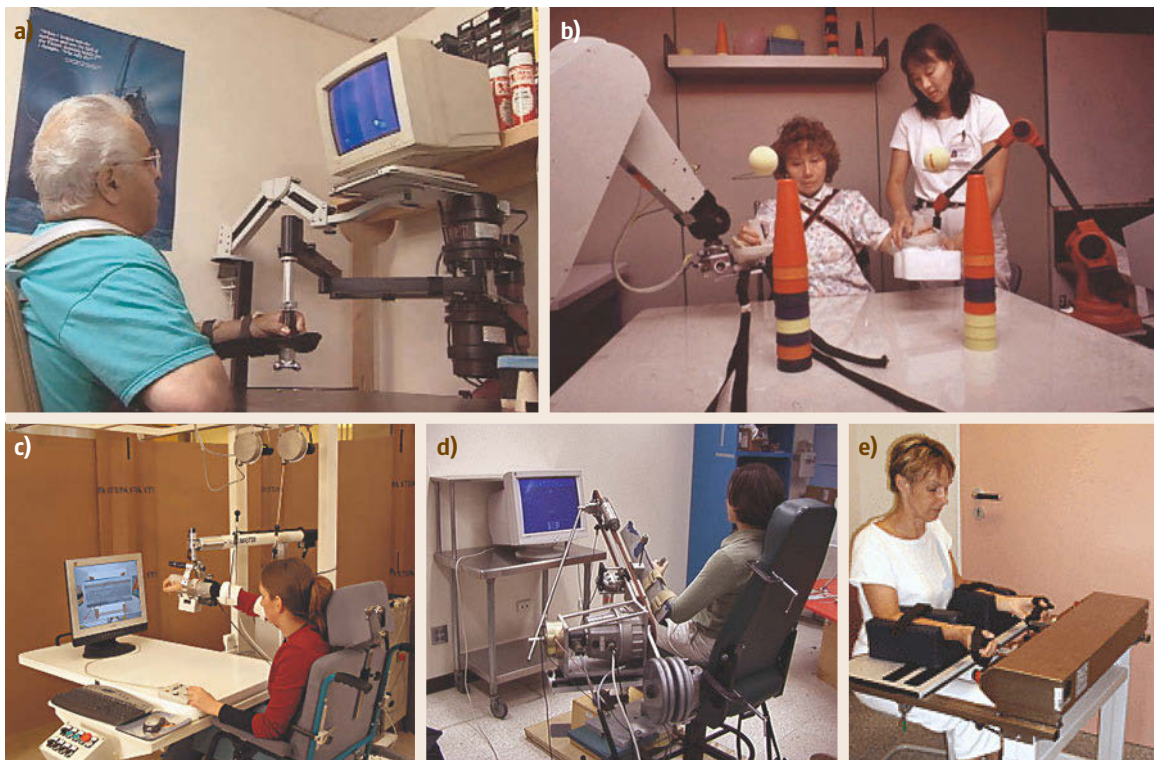


Fig. 64.6a–e Arm-therapy robotic systems that have undergone extensive clinical testing; (a) MIT-MANUS, developed by Hogan, Krebs, and colleagues at the Massachusetts Institute of Technology (USA), (b) MIME, developed at the Department of Veterans Affairs in Palo Alto in collaboration with Stanford University (USA), (c) GENTLE/s developed in the EU, (d) ARM-Guide, developed at the Rehabilitation Institute of Chicago and the University of California, Irvine (USA), and (e) Bi-Manu-Track, developed by Reha-Stim (Germany)

ventional therapy and a brief, sham exposure to the robot [64.92]. The robot group patients received the additional robotic therapy for an hour each day, five days per week, for several weeks. The robot group recovered more arm movement ability than the control group according to clinical scales, without any increase in adverse effects such as shoulder pain. The improvements might subjectively be characterized as *small but somewhat meaningful to the patient*. The improvements were sustained at a three-year follow-up.

This first study with MIT-MANUS demonstrated that acute stroke patients who received more therapy recover better, and that this extra therapy can be delivered by a robotic device. It did not answer the question as to whether the robotic features of the robotic device were necessary. In other words, it may have been that patients would have also improved their movement ability if they had practiced additional movements with MIT-MANUS with the motor's off (thus making it equivalent to a computer mouse), simply by virtue of the increased dose of movement practice stimulating use-dependent plasticity. Thus, while this study indicated the promise of robots for rehabilitation therapy, it did not close the gap of knowledge as to how external mechanical forces provoke use-dependent plasticity.

Subsequent studies with MIT-MANUS have confirmed that robotic therapy can also benefit chronic stroke patients [64.93]. The device has been used to analyze different types of therapies, for example, to compare assisting movement versus resisting movement in chronic stroke subjects, but with inconclusive results: both types of therapies produced benefits [64.90]. The device has also been used to compare assistive robot therapy with another technological approach to rehabilitation – electrical stimulation of finger and wrist muscles [64.94]. Again, significant benefits were found for both therapies, and those benefits were specific to the movements practiced, but the benefits were not significantly different between therapies. We note that the lack of a significant difference in these studies may simply be due to the limited number of patients who participated in these studies (i.e., inadequate study power), rather than a close similarity of the effectiveness of the therapies.

As mentioned above, the MIT-MANUS device was recently tested in a multisite clinical trial funded by the Department of Veterans Affairs in the United States [64.50]. This study compared clinical outcomes in chronic stroke survivors who were randomized to three groups: usual care, robot-assisted therapy with arm, wrist, and hand modules, and one-on-one therapy with a rehabilitation therapist that was dose matched to the robotic therapy in terms of the number of move-

ments achieved per therapy session. The robot-assisted therapy group improved their movement ability more than the usual care, and about the same as the dose-matched group. This is an important finding for the field, as it demonstrated with the highest scientific rigor that robotic therapy was about as effective as an intense, therapist-delivered therapy.

A cost-benefit analysis of this study suggested that although both robotic and intense, therapist-based therapies were more expensive to deliver than usual care, it reduced long-term follow-up costs, so that the total cost of care of the patients was the same over the duration of the study [64.95]. Thus, as the cost of robotic therapy devices decreases, it should be possible to provide patients with improved outcomes while reducing the cost of therapy – another important finding.

MIME

Another early system to undergo clinical testing was the **MIME** (mirror-image movement enhancer) system, which used a Puma-560 robot arm to assist in movement of the patient's arm [64.96]. The device is attached to the hand through a customized splint and a connector that is designed to break away if interaction forces become too large. Compared to MIT-MANUS, the device allows more naturalistic motion of the arm because of its six degrees of freedom (**DOF**), but must rely on force feedback so that the patient can drive the robot arm. Four control modes were developed for **MIME**. In the passive mode, the patient relaxes and the robot moves the arm through a desired pattern. In the active assist mode, the patient initiates a reach toward a target, indicated by physical cones on a table top, which then triggers a smooth movement of the robot toward the target. In the active-constrained mode, the device acts as a sort of virtual ratchet, allowing movement toward the target, but preventing the patient from moving away from the target. Finally, in the mirror-image mode, the motion of the patient's less impaired arm is measured with a digitizing linkage, and the impaired arm is controlled to follow along in a mirror-symmetric path. The initial clinical test of **MIME** found that chronic stroke patients who received therapy with the device improved their movement ability about as much as patients who received conventional table-top exercises with an occupational therapist [64.96]. The robot group even surpassed the gains from human-delivered therapy for the outcome measures of reaching the range of motion and strength at key joints of the arm. A follow-on study attempted to elucidate which of the control modes or what combination of **MIME** exercises caused the gains, but was inconclusive [64.97]. A multisite randomized control of **MIME** again funded by the Department of Veterans Affairs compared the

effect of a high-dose (30 h) of additional therapy with **MIME**, to a lower dose (15 h), to 15 h of additional conventional therapy in 54 acute stroke patients [64.98]. Gains in the primary outcome measure, the Fugl-Meyer assessment, were not significantly different between the groups at the 6-month follow-up, although there the actual dose of robotic therapy patients received predicted their recovery.

ARM Guide

The question of the effect of robot forces on movement recovery was also left unresolved by a study with another device, the **ARM Guide**, which is a trombone-like device that can be oriented then locked in different directions, and can assist people in reaching in a straight line. Chronic stroke patients who received assistance during reaching with the robot improved their movement ability [64.99]. However, they improved about as much as a control group that simply practiced a matched number of reaches without assistance from the robot. This suggests that movement effort by the patient is a key factor for recovery, although the small sample size of this study limited the ability to resolve the size of the difference between guided and unguided therapies.

Bi-Manu-Track

Perhaps the most striking clinical results generated so far have come from one of the simplest devices built. Similar to a design proposed previously by Lum et al. [64.39], the Bi-Manu-Track uses two motors, one for each hand, to allow bimanual wrist-flexion extension [64.100]. The device can also assist in forearm pronation/supination if it is tilted downward and the handles are changed. In an extensive clinical test of the device, 22 subacute patients (i.e., 4–6 weeks after stroke) practiced 800 movements with the device for 20 minutes per day, five days per week for six weeks [64.100]. For half the movements, the device drove both arms, and for the other half, the patient's stronger arm drove the motion of the more impaired arm. A control group received a matched duration of electrical stimulation (**ES**) of their wrist extensor muscles, with the stimulation triggered by voluntary activation of their muscles when possible, as measured by electromyography (**EMG**). The number of movements performed with **EMG**-triggered **ES** was 60–80 per session. The robot-trained group improved by 15 points more on the Fugl-Meyer scale, a standard clinical scale of movement ability with a range from 0 to 66 points in upper extremity function. It assigns a score of 0 (cannot complete), 1 (completes partially), or 2 (completes normally) for 33 test movements, such as lifting the arm without flexing the elbow. For compar-

ison, reported gains in Fugl-Meyer score after therapy with the MIT-MANUS and **MIME** devices ranged from 0 to 5 points [64.101].

Other Early Devices to Undergo Clinical Testing

Other early devices to undergo clinical testing are as follows. The GENTLE/s system uses a commercial robot, the HapticMaster, to assist in patient movement as the patient plays video games. The HapticMaster allows four degrees of freedom of movement and achieves a high bandwidth of force control using force feedback. Chronic stroke patients who exercised with GENTLE/s improved their movement ability [64.102, 103]. The Rutgers **ARM** robotic device uses low-friction pneumatic cylinders to help extend or flex the fingers, and has been shown to improve hand movement ability of chronic stroke subjects [64.104]. Simple force-feedback controlled devices, including a 1-DOF wrist manipulator and a 2-DOF elbow-shoulder manipulator, were also recently shown to improve movement ability of chronic stroke subjects who exercised with the devices [64.105]. A passive exoskeleton, the T-WREX arm orthosis, provides support to the arm against gravity using elastic bands, while still allowing a large range of motion of the arm [64.106]. By incorporating a simple hand-grasp sensor, this device allows substantially weakened patients to practice simple virtual reality exercises that simulate functional tasks such as shopping and cooking. Chronic stroke patients who practiced exercising with this nonrobotic device recovered significant amounts of movement ability, comparable with the Fugl-Meyer gains seen with MIT-MANUS and **MIME**. A randomized controlled trial of T-WREX in 28 chronic stroke subjects compared therapy with the device to conventional, table-top therapy [64.107] and found that the device was slightly more effective in improving patient's motor ability at the six-month follow-up according to the primary outcome measure, the Fugl-Meyer score, and that patients strongly preferred exercising with the device. T-WREX has been commercialized as the Armeo Spring upper extremity training device by Hocoma, and was in use in over 500 clinics as of early 2014, with published reports studying its use for individuals with multiple sclerosis [64.108], **SCI** [64.109], and proximal humeral fracture [64.110]. NeReBot is a 3-DOF wire-based robot that can slowly move a stroke patient's arm in spatial paths. Acute stroke patients who received additional movement therapy beyond their conventional rehabilitation therapy with NeReBot recovered significantly more movement ability than patients who received just conventional rehabilitation therapy [64.111]. RehaRob uses an industrial robot arm to mobilize patients' arms along arbitrary trajectories following stroke [64.112].

Further Research and Developments on Robotic Therapy for the Upper Extremity

One recent trend in the field is to develop devices that can provide therapy for a larger number of degrees of freedom of the arm. For example, at the high end of cost and complexity are the ARMin [64.113], Pneu-WREX [64.114], and BONES [64.115], which are exoskeletons that accommodate nearly naturalistic movement of the arm while still achieving a wide range of force control. A system that couples a immersive virtual reality display with a haptic robot arm is described in [64.116]. A wearable exoskeleton driven by pneumatic muscles is described in [64.117]. Several other exoskeletal machines have been proposed to jointly train arm and wrist, such as the CADEN-7, an anthropometric 7-DOF powered exoskeleton system [64.118]; the SUEFEL-7, which exploits EMG signals to adjust impedance parameters [64.119]; a lightweight exoskeleton described in [64.120], and the highly redundant 9-DOFs machine introduced in [64.121].

Another area of active development in robotic therapy devices for the upper extremity is to devices that can be used at home or in rank-and-file clinics. For example, at the lower end of cost/complexity are devices that use force feedback joysticks and steering wheels with a view toward implementation in the home [64.114–125]. In 2008, a planar machine for upper limb rehabilitation designed for delivering at-home neurorehabilitation, namely CBM MOTUS, was developed and patented [64.126] (Fig. 64.7). Such a device has low inertia and highly isotropic behavior. Recently, a passive module has been developed to be installed on the CBM-MOTUS, able to further reduce robot perceived inertia when the machine is moved by the patient, while being highly rigid when the machine assists the patient's movements.

As far as wearable robotic systems for the upper limb are concerned, Hocoma engineered and com-

mercialized the ARMEO power system, and also the ArmeoSpring and ArmeoBoom machines [64.108].

A third area in robotic therapy devices for the upper extremity that has received increased attention is to develop devices for hand rehabilitation, since hand movement ability is essential for functional recovery. Examples of recent, novel robotic devices for the hand are the Haptic Knob for grasping and wrist pronation/supination [64.128]; the HandCARE, a cable-actuated rehabilitation system [64.129]; a device for repeating controlled passive movements of paralyzed fingers given in [64.130]; the exoskeletal machines HWARD [64.131], and HEXORR [64.132] to help open and close the hand; the 18-DOFs highly redundant Gifu Haptic Interface [64.133], able to produce adduction–abduction and flexion–extension finger movements. Other devices are presented in [64.134–138], and a review of robotic therapy of the hand is given in [64.139]. One robotic therapy system for the hand incorporates the idea of using visual feedback distortion to enhance motivation of patients during movement therapy [64.140]. A few commercial machines are available, such as the Reha-Digit, Amadeo, and ManovoSpring.

Based on the availability of modular hand, wrist, and shoulder–elbow therapeutic robotic devices, some recent studies tried to tackle the fundamental question of whether proximal or distal treatment differentially affect the recovery of arm/hand function. For more information of these preliminary studies, see references [64.100, 141, 142].

An important recent development in robotic therapy devices is the development of devices that can be used in conjunction with the instrumentation needed to measure neurophysiological signals, such as functional magnetic resonance imaging (fMRI)-compatible systems [64.143, 144] or, more generally, brain-imaging (BI)-compatible robotic systems that can be used in conjunction not only with fMRI but also with magne-

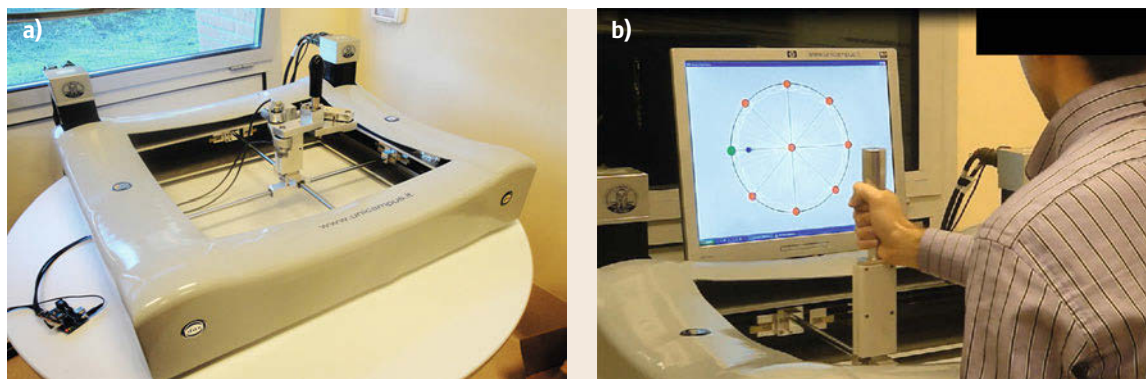


Fig. 64.7a,b CBM Motus robot for upper limb rehabilitation (after [64.127])

toencephalography (MEG), transcranial magnetic stimulation (TMS), repetitive TMS (rTMS), transcranial direct current stimulation (tDCS), near infrared spectroscopy (NIRS) and other brain imaging and stimulation equipment. Such devices are notable because they will allow a systematic scientific study of neural recovery during robotic therapy. Developing these devices requires dealing with the problems of electromagnetic compatibility and interaction.

Recently, a few fMRI-compatible devices for hand rehabilitation have been designed to acquire functional imaging while performing therapeutic exercises, such as the exoskeletal machine in [64.145]; the pneumatic actuated 2-DOF device to help wrist pronation/supination and hand open/closure in [64.146]; machines driven by electro-rheological fluids, able to provide a variable resistance to patient motion [64.147]; the planar device to help move fingers described in [64.148]. A passive fMRI-compatible manipulator morphologically similar to MIT-MANUS has been developed and tested to acquire functional imaging in [64.149]. Another study proposed the applications of a brain-computer interface (BCI) therapy approach on a cohort of stroke patients, [64.150]; a magnetoencephalography-based BCI system is used which in turn raised or lowered a screen cursor in the direction of a target. Results suggest that volitional control of neuromagnetic activity features recorded over central scalp regions can be achieved with BCI training after stroke.

Finally, the primary paradigm that has been tested so far with upper extremity robotics is to assist patients in moving, a strategy which may in some cases have the unintended affect of causing patients to *slack* [64.151]. In general, the field is still relatively undeveloped in its ability to identifying the most appropriate forms of robotic intervention given the nature of the impairment and the patient. For example, an approach opposite to physical assistance, which is using robotic force fields to amplify the kinematic errors of stroke patients during reaching, may provoke novel forms of the adaptation of those patterns [64.4, 152]. A major emphasis of the field in the next 10 years will be improving the mechanistic understanding of how robotic interaction influences brain plasticity.

64.2.4 Robotic Therapy for Walking

Scientific evidence that gait training improves the recovery of mobility after neurologic injury started to accumulate in the 1980s through studies with cats. Cats with SCI can be trained to step with their hind limbs on a treadmill with the partial support of body weight and assistance of leg movements [64.153, 154].

Following the animal studies, various laboratories developed a rehabilitation approach in which the patient steps on a treadmill with the body weight partially supported by an overhead harness and assistance from therapists [64.155–158]. Depending on the patient's impairment level, from one to three therapists are needed for BWSTT (body-weight supported treadmill training), with one therapist assisting in stabilizing and moving the pelvis, while two additional therapists sit next to the treadmill and assist the patient's legs in swing and stance. This type of training is based on the principle of generating normative, locomotor-like sensory input that promotes the functional reorganization and recovery of the injured neural circuitry [64.159]. In the 1990s, several independent studies indicated that BWSTT improves stepping in people with SCI or hemiplegia after stroke [64.155–157].

Gait training is particularly labor-intensive and strenuous for therapists, so it is an important target for automation. The efforts of roboticists have been especially focused on BWSTT rather than over-ground gait training because BWSTT is done on a stationary setup in a well-defined manner and thus can be more easily automated than over-ground gait training. Randomized, controlled clinical trials have shown that BWSTT is comparable in effectiveness to conventional physical therapy for various gait-impairing diseases [64.160–166]. These trials support the efforts toward the automation of BWSTT, as the working conditions of physical therapists will improve if the robots do much of the physical work, which, in the case of BWSTT, actually leads to occasional back injuries to therapists. Usually, only one therapist is needed in robot-assisted training, for the tasks of helping the patient into and out of the robot and monitoring the therapy. In the case of SCI patients, a small randomized, controlled trial [64.161] reported that robotic-assisted BWSTT with a first-generation robot required significantly less labor than both conventional overground training and therapist-assisted BWSTT, with no significant difference found in effectiveness.

Gait-Training Robots in Current Clinical Use

Some gait-training robot systems are commercially available and are used for therapy in several clinics worldwide, such as the gait trainer GT-I [64.46], the Lokomat [64.45] the ReoAmbulator, the Loko-Help [64.167], and the G-EO System [64.168] (Fig. 64.3a–e).

Of these robots, the GT-I (commercialized by Reha-Stim) is the one that departs most from therapist-assisted BWSTT, since it interacts with the patient's lower limbs through two footplates rather than acting on the shank as human therapists do. It also ap-

pears to depart more from natural walking because the footplate principle substantially alters the sensory cues of the foot impact with the ground or treadmill band. The GT-I footplates are driven by a singly actuated mechanism that moves the foot along a fixed gait-like trajectory with a doubled crank and rocker system [64.46]. The stride length can be adjusted between sessions by changing gears. The body weight is unloaded as needed by an overhead harness. The torso is moved sagittally in a phase-dependent manner by ropes attached to the harness and connected by another crank to the foot crank. The GT-I is currently installed in dozens of clinics, mainly in Europe. One randomized, controlled study has been reported that tested the GT-I with 30 subacute stroke patients [64.169]. The robot group improved their overground walking ability more than the control group, although differences were not significant at a 6-month follow-up. A total of 80% of the patients said they preferred training with the robot rather than the therapists because training with the robot was less demanding and more comfortable. The other 20% of patients stated that swinging of the paretic limb seemed less natural and thus less effective when training with the robot. Robot-assisted training required an average of one therapist per patient, while therapist-assisted training required two therapists per patient on average. A follow-up, randomized controlled study comparing conventional training plus robotic training with the GTI, to a time-matched amount of conventional training alone with subacute stroke patients, found that the group that received some robotic training recovery walking ability to a great extent [64.170]. More recent clinical tests with the GT I are reported in [64.171].

The Lokomat (commercialized by Hocoma) is a robotic exoskeleton worn by the patients during treadmill walking [64.45]. Four motorized joints (two per leg) move hip and knee. The actuators consist of ball screws connected to dc motors. The legs are driven in a gait-like pattern along a fixed position-controlled trajectory. The device attaches to the thighs and shanks through padded straps. A parallelogram mechanism allows the vertical translation of the patient's torso, restricting lateral translation. The patient's body weight is actively unloaded as needed through an overhead harness. The Lokomat is currently being used in over 100 clinics worldwide. In 2005, Wirz et al. [64.85] reported preliminary results of robot-assisted BWSTT with the Lokomat in 20 chronic incomplete SCI patients. The improvements in overground walking speed and endurance were statistically significant: approximately 50% gain on average in the 16 patients who were ambulatory before training. There were no significant changes in the requirement

of walking aids, orthoses, or external physical assistance. The improvements appear to be comparable to those achieved by similar SCI patients who received therapist-assisted BWSTT [64.161, 172]). For the case of stroke patients, however, therapy with the Lokomat was beneficial but about half as effective as treadmill-based or therapist-based training in improving overground gait velocity and endurance [64.173, 174].

The ReoAmbulator (commercialized by Motorika and marketed in the United States as AutoAmbulator) consists of two robotic arms that assist patients to step on a treadmill with their body weight supported as needed. The interface to the patient's legs is through straps at the thigh and ankle. The ReoAmbulator is currently being used in at least 57 HealthSouth rehabilitation centers, all of them in the United States, but little data have been published concerning its use.

The LokoHelp (commercialized by LokoHelp Group) assists users' feet motion along physiological trajectories while walking on a treadmill, also providing body weight support. Clinical trials [64.167, 171, 175] show that therapeutic outcomes are similar to manual training with reduced therapist effort.

The G-EO system (commercialized by Reha Technology) is also based on the footplate principle as for the GT I system. Studies with stroke survivors [64.176], patients with SCI [64.177] and with Parkinson's disease [64.178] have recently shown the value of this particular device.

Further Research and Developments on Robotic Therapy for Walking

Several groups worldwide are working toward improving gait-training robotic technologies. A great deal of effort has been made to incorporate and investigate the ability to assist as needed [64.72, 179–183], that is, the ability of the robot to let the patients contribute to the locomotor efforts as much as they are able. This is likely essential for maximizing locomotor plasticity [64.184]. Some effort has also been directed toward adding more active DOFs, particularly for torso manipulation [64.182, 185]. These robotic tools are needed not only for their potential clinical use in therapy, but for studying what aspects of the assistance are important for effective gait training and how best to control and implement them with robotic devices.

The team responsible for the GT-I has developed the Haptic Walker [64.179], which maintains the permanent foot/machine contact but allows the footplates to move along 3-DOF trajectories. In addition, it incorporates force feedback and compliance control, as well as haptic simulation of ground conditions (e.g., stair climbing).

An advanced version of the Lokomat integrates force sensors and automatic adaptation of gait patterns to allow for a reduction of the interaction effort between patient persons and machine [64.180]. It has been tested on unimpaired persons and SCI patients, who were able to influence the gait trajectories toward a more desired motion by means of their own motor activity [64.180, 186].

PAM is a 5-DOF robot for torso manipulation, and POGO is a leg robot with 2-DOF per leg. PAM's and POGO's actuators are pneumatic, which cost less than electric motors and have higher power-to-weight ratios [64.185]. The robots' ability to control forces and yield to patients and/or therapists has been tested with unimpaired and SCI participants [64.187]. Of particular note here is the development of an adaptive synchronization algorithm that allows these compliant robots to provide assistance at the right time as the participants varies the timing or size of steps.

Based on the string-puppet principle, the String-Man achieves weight bearing and compliant 6-DOF torso manipulation by means of seven wires and a force sensor on each wire [64.182]. In addition, a control scheme has been designed for the String-Man to control both the zero-moment-point location and the ground reaction force with help of foot force sensors.

Veneman et al. [64.189] developed the LOPES exoskeleton (lower extremity powered exoskeleton) visible in Fig. 64.8. In this system, two horizontal pelvis translations are actuated, while the vertical motion is left free and weight is compensated. Furthermore, the LOPES have three actuated rotational joints per leg: two at the hip and one at the knee. The actuation system for hip and knee flexion/extension [64.183] combines Bowden cables with series elastic actuation. The Bow-

den cables allow the motors to be mounted remotely in a fixed position, thus reducing the mass to be moved on the exoskeleton links. The spring element connecting the Bowden cables with the joint allows the closing of a torque feedback control loop with a position sensor that measures the spring elongation, a concept inspired from the series elastic actuators (SEAs) described by Pratt and coworkers [64.190].

Veneman et al.'s experimental results on LOPES SEAs show that adequate torque control bandwidth was achieved by the prototype of their Bowden-cable-based actuation design [64.183], so that the robot can execute both a stiff, position-dominated robot-in-charge mode and a compliant, low-impedance patient-in-charge mode. Some results on the testing of the LOPES exoskeleton are presented in [64.192–194].

The FET European project *Evolving Morphologies for Human–Robot Symbiotic Interaction* (EVRYON) investigated a novel approach for the design of wearable robots in which robot morphology and control are co-evolved in a physics-based simulation environment to achieve a symbiotic interaction, with useful behaviors (walking patterns) emerging from the dynamic interaction between the robot and the human body. To narrow the search space, an atlas of topologies of robot architectures assisting hip and knee flexion/extension was produced [64.195], showing that only ten topologies are capable of providing independent assistance to hip and knee if the number of robot links is not higher than 4 and only revolute joints are considered. The kinematic structures (morphologies) descending from such topologies do not require the alignment of robot and human joints (nonanthropomorphism), thus possibly shortening calibration time and limiting wearability issues. Among the abovementioned ten topologies, only

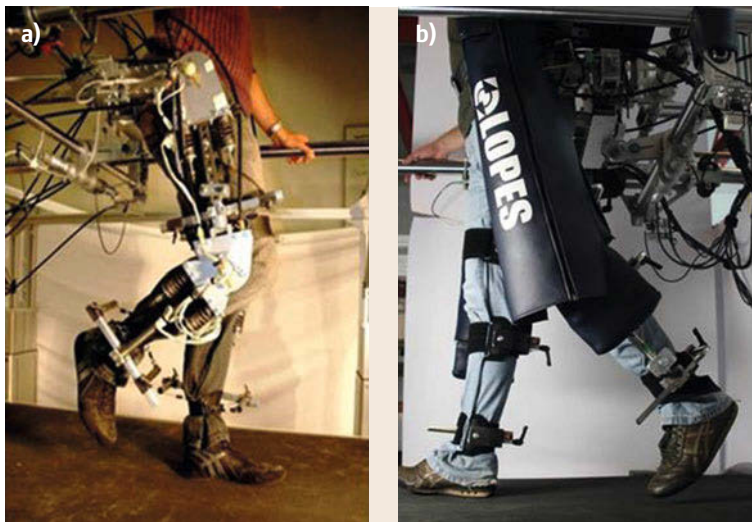


Fig.64.8a,b LOPES (lower-extremity powered exoskeleton) device for gait training and assessment of motor function in stroke survivors (after [64.188])

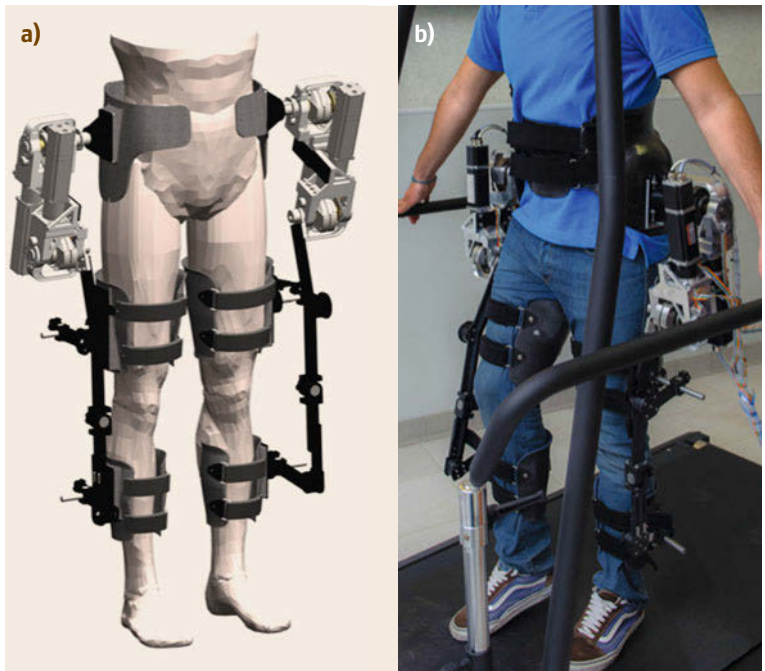


Fig.64.9a,b EVRYON/LENAR.
(a) Wearable robot to assist hip and
(b) knee flexion/extension through
series elastic actuators (after [64.191])

one allows us to mechanically (intrinsically) minimize unwanted shear forces while keeping encumbrance low. A morphology belonging to this topology class was optimized to minimize reaction forces on the human body [64.196] and to maximize wearability and back-drivability [64.197]. Based on this study, the lower extremity nonanthropomorphic robot (LENAR) [64.191] was developed (Fig. 64.9), incorporating custom-made series-elastic actuators for a robust interaction control [64.198].

A different approach to gait training was taken with the KineAssist device [64.199]. KineAssist (Fig. 64.10) is a motorized mobile platform that follows the patient and therapist as they move overground and incorporates a smart brace that compliantly supports the patient's trunk and pelvis. This smart support is designed to allow the therapist to adjust its stiffness from fully rigid down to fully compliant. Within a safety zone, the fully compliant mode allows patients to challenge the limits of their stability. A compliant virtual wall catches the patients when they lose balance. The location of this virtual wall is also adjustable. The body weight can be unloaded as needed. The main advantage of this system is the possibility for the therapist to work in close contact with the patient while cooperating with the robotic system, which deals with the crucial, basic task to keep the patient stable and safe. From this research platform, HDT Robotics began commercialization of the KineAssist-MX. Actuation and sensors allow interactive force-field environments so that a wide variety of

challenging mobility experiences can be delivered to the user.

Other efforts include *Ferris* and coworkers [64.202], who are developing foot, ankle, knee, and hip orthoses actuated by artificial pneumatic muscles that may possibly be used to assist in gait training. The Rutgers Ankle is a 6-DOF pneumatic system based on a Stewart Platform that allows exercise of the ankle [64.203]. Also in the United States, Agrawal's group proposes the use of gravity-balancing leg orthoses for people with gait impairments to practice walking [64.204]. Their designs allow the orthoses to passively support the gravity torque required at the patient's joints. This approach would have the advantage of being safer than powerful robots for clinical use. They have also extended their design



Fig. 64.10 KINE ASSIST for unobtrusive support to patients, allowing them to walk on their own, or with variable levels of support (after [64.200])

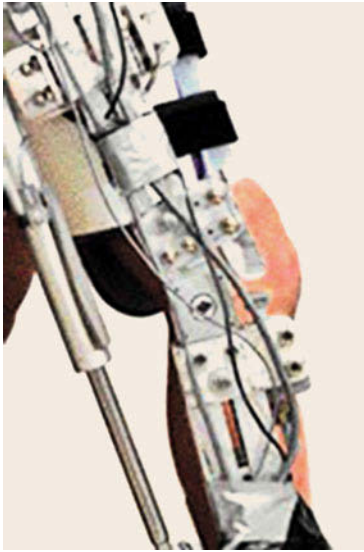


Fig. 64.11 Active leg exoskeleton (ALEX) to supplement traditional rehabilitation therapy (after [64.201])

walks in a circle [64.206]. Banala et al. developed the treadmill-based rehabilitation robot ALEX [64.207], as seen in Fig. 64.11. In this system, hip and knee joints are actuated in the sagittal plane while hip abduction/adduction and ankle motion are spring-loaded. More details and further examples of robotic systems for walking therapy are reported in [64.208].

Other Robotic Movement Therapy Approaches

As reviewed earlier, most of the work to date in robotic therapy devices has focused on robots that are attached to patients to assist them in practicing reaching or walking exercises. Other early proposals for using robots for movement therapy included using two planar robot arms to carefully control continuous passive motion of the knee following joint surgery [64.37], and using a multiaxis robot arm to place targets for patients doing reaching exercises [64.209]. An emerging approach toward robotic movement therapy is to provide the therapy at a distance, in a form of telerehabilitation, in order to improve accessibility to the therapy [64.81, 123, 210]. Non-contacting, socially assistive robots, as reviewed in Chap. 73, may play an important role in motivating and monitoring therapy.

to include actuators with reduced torque requirements [64.205]. A robot has been used to provide graded body weight support as a patient who cannot bear full body weight because of a medical problem

64.3 Aids for People with Disabilities

Enabling technologies assist people with disabilities to achieve a quality of life on a par with able-bodied individuals through increased functional independence. The main issue with most such technologies is that disability has a highly individualized impact: a solution for one person will not work for someone else, even if their disabilities appear clinically similar.

64.3.1 Grand Challenges and Enabling Technologies

The more a disability impacts function, the more costly the technical intervention tends to be, since the consumer market cannot benefit from economies of scale if each solution must be individualized. As an extreme example, an electric wheelchair with individualized padding, motorized recliner, and customized joystick control costs as much as a mass-produced mid-sized automobile, but has a fraction of the electronics, robustness, and functions. A grand challenge for assistive, enabling technologies is to find a means to make mass-personalization possible, as it has been in the automotive industry, for example. One component is designer focus. If we can re-badge *assistive technology* as *design for well-being products*, the change in focus from

fixing people to improving their quality of life will have the effect of mainstreaming disability itself so that manufacturers of consumer equipment tend to develop products that can explicitly accommodate a much wider range of functional abilities and therefore provide benefit to a larger, overall less-able, consumer base. As the average age of the baby boomers climbs into retirement years with significant disposable income, this segment will compel the market into providing better solutions to their well-being needs.

Another grand challenge is robotic autonomy. Especially for persons with reduced communication, physical and/or cognitive abilities, a rehabilitation robot will need to have sensory (e.g., vision, auditory) and motor capabilities, combined with its own software processing capabilities (also termed artificial intelligence), that make it a sufficiently safe and capable system to coexist with and benefit humans. This challenge will to some extent be dependent on continuing increases in computer-processing power, and also specifically dependent on the algorithmic developments that issue from the community of robotics researchers.

For instance, several advanced navigation assistive tools for blind and visually impaired persons have

been developed by exploiting knowledge and technologies directly derived from research on autonomous robot navigation; as a sample, *Borenstein and Ulrich* in 1997 developed the GuideCane [64.211], an intelligent cane, based on ultrasound proximity sensor technology, which was designed to help blind or visually impaired travellers to navigate safely and quickly among obstacles and other hazards faced by blind pedestrians [64.212].

Research on robotic aids (namely *physically assistive robots* or, also, *contact assistive robots*) has so far primarily targeted persons with mobility and manipulation limitations, rather than children and adults with cognitive impairments [64.213, 214]. However, increases in the prevalence of cognitive impairments related to aging will make the latter focus increasingly important. *Socially assistive robots*, also named *contactless assistive robots*, are emerging assistive systems that focus on helping human users through social rather than physical interaction (see Chap. 73 for more details on socially assistive robots). Research has been limited to the mobility focus due to the difficulty of designing and developing intrinsically safe robots that can coexist with people and exhibit a certain amount of autonomy while performing useful work. Robots, therefore, today rely on user vigilance and explicit control to be safe. If the user does not have the cognitive capacity to evaluate a robot's safety situation or the ability to communicate efficiently, then the positive value of a function-enhancing robot is nullified by the harm that it could inflict on the user or bystanders. Coupled with the fact that the design of interfaces to personal robots is still in its infancy, a challenge for robotic aid developers is a significant improvement in intrinsic safety without a decrease in function (strength, speed, etc.) from what is typical today in industrial robotics.

To address some of these challenges, the US government, through NSF, NIH and other federal agencies, in 2011 issued a call for a \$ 50 million per year, 5-year program called the National Robotics Initiative (NRI) [64.215]. The realization of co-robots acting in the direct support of individuals and groups. A substantial amount of this funding is focused on healthcare of the future.

Disabilities and Functional Limitations Served by Robotic Aids

Assistive robots have been designed for people who have become severely disabled as a result of, for example, muscular dystrophy or a high-level SCI, for children who have CP, and more generally for anyone who lacks the ability to manipulate household objects. A market research study conducted 10 years ago, specifically for rehabilitation robotics clients, con-

servatively projected a US market of 100 000 people [64.216]. With the incidence of disability increasing exponentially, and the niches that robots can fill in rehabilitation applications multiplying with advances in robotics and rehabilitation science, it is clear that the market for rehabilitation robotics can only continue to increase.

Human–Robot Interface Design for Assistive Robots

A fundamental difference between using industrial and assistive robots is the interface required to command, control, and ultimately benefit from them. An industrial robot commonly has a combination of a manual controller and a programming language interface to allow an operator to teach a robot where to go and to enter the specific motion, grasping, tool changing, and error-recovery steps it must follow repeatedly in its factory automation scenario. An assistive robot, on the other hand, typically has three main differences and challenges:

1. The operator is not by definition a roboticist or engineer, so the interface must make accessible all the functions of the robot to allow its user to complete the required tasks.
2. The user of a rehabilitation robot is, by definition, a person with a disability, which means that physical, sensory, communication, and/or cognitive limitations in accessing the commands and controls of a robot need to be handled on a systems level by the designers of robots and their interfaces, with critical attention to universal design principles, and
3. All rehabilitation robots require individualization of the interface to each user by the engineering and therapy professionals in charge of prescription and fitting, since disabilities vary considerably in how they restrict adaptability to standard configurations [64.217].

Interfaces of assistive robots consist of the software and hardware components conceived to enable a person with a disability to interact with an assistive device, thus tapping into residual communication capabilities of each user. For example, many people with tetraplegia retain the ability to move a hand, arm, foot, or the head in a repeatable, even if range-limited way, and possibly even in two axes, such as forward/backward and left/right. With a proper placement of pushbuttons, a joystick, or noncontact position measurement device, a rehabilitation engineer and therapist can develop a custom solution for each of their clients with disabilities to control a wheelchair computer and robot. In addition, adaptive hardware and software for controlling a computer, such as head-position cursor control,

eye-trackers, speech recognition systems, trackballs and special keyboards, can be used to provide access to computer-based robot functionality.

Even more important than for able-bodied computer and robot users, redundancy in input modality is important for persons with disabilities to prevent a system from becoming inoperable due to a simple interface malfunction or calibration problem. Providing two means of creating a mouse-click action (for example, a separate button placed next to a cursor-control trackball, as well as dwell time on a software *button* on-screen), even if one is inherently slower than the other, allows continued and uninterrupted use of the computer without outside assistance even if one of the two fails.

For therapy robots, physical interfaces resemble those for physical and occupational therapy equipment, in general, and have a commonality with sports equipment interfaces as well, with adjustable hook-and-loop-type straps, heat-formable plastic cuffs, soft rubber, foam-based materials, and durable coverings for abrasion resistance and long wear. After a session or two for fitting and adaptation, a person using a therapy robot can often use the same interface for a long period of time.

In summary, the keys to interface design are customizability, individualization, functional redundancy, adaptability, and patience in getting the interface to a comfort and functional level appropriate for the effective use of the robot.

64.3.2 Types and Examples of Assistive Rehabilitation Robots

As mentioned in the Introduction, assistive robots can be divided into three main categories: manipulation aids, mobility aids, and cognitive aids. Each can be subdivided as follows. Manipulation aids are commonly divided into fixed, portable, and mobile subtypes. Mobility aids are divided into electric wheelchairs with autonomous navigation features and smart walkers. Cognitive aids are divided into communication aids such as pet robots and autonomous caretaker robots. These categories are introduced below, and representative systems that have undergone scientific user studies or are commercial products are presented (Fig. 64.12a–c). Other examples are mentioned in Sect. 64.1.3.

Manipulation Aids: Fixed-Base

Common robots of this type are **ADL** and vocational manipulation aids and kitchen robots. In the United States, the professional vocational assistive robot (**ProVAR**) is a research prototype based initially on a PUMA-260 robot arm mounted on a 1 m



Fig. 64.12a–c Workstation-type robots: (a) AfMaster, developed by the French Muscular Dystrophy Association, (b) ProVAR, developed at the VA Palo Alto Rehabilitation R&D Center, and (c) Handy-1, developed by RehabRobotics, Ltd. (UK)

transverse overhead track that allows the robot to manipulate objects and operate devices on side shelves and the table-top, bringing objects (like a drink of water or throat lozenge) to the robot's operator. The interface is via a JAVA/VRML plug-in to a common Internet browser, delivering high-level control to disabled office workers in a conventional pull-down menu and a control screen interface [64.27, 218]. This system and its predecessor DeVAR have been field tested by over 50 subjects at 5 rehabilitation clinics to assess feasibility and acceptability [64.219, 220]. At a cost of over US \$ 100 000 currently, there are currently no plans for eventual product introduction.

In the EU, following a development path parallel to ProVAR's, there is the AfMASTER/RAID workstation, whose concept, instead of being built into a workstation, includes a 2 m × 3 m robot work area in the user's office to store objects and place appliances, next to the user's own office space. The system has been developed

over a 20-year span and was briefly in limited production [64.29] but is no longer offered for sale.

The kitchen robot, Giving-A-Hand, developed at the Scuola Superiore Sant'Anna in Pisa, Italy, is a low-degree-of-freedom device for mounting on the front rail of a kitchen counter and able to move food containers to and from appliances, such as refrigerators and ovens [64.221]. With an integrated control system, it can also make use of the internal controls of the devices to, for example, set cooking times and open doors.

The UK-developed Handy-1 is a domestic robot with 3-DOF designed for one-switch operation by persons with CP [64.30]. Originally designed to allow a person to eat a meal one bite at a time, its application areas have been extended to face hygiene and cosmetics. A commercial product selling for about US\$ 6000, it has been a commercial success due to its simplicity and application focus. An even simpler feeding robot, the UK's electric Neater Eater [64.20] is for sale worldwide at about US\$ 5000, and is designed for eating only.

In [64.222], an overview of manipulation robotic aids is provided. They are classified through five criteria, based on robotic arm usage scenarios and surveys. In particular, new assistive manipulators have recently been developed that address interaction safety as a priority criterion in their design. Take for instance JACO [64.223], iARM [64.224] and RAPUDA [64.225] as examples of robot arms achieving safety by limiting the performance of the robotic arm in terms of arm-movement speed and acceleration in space, end-effector force and maximum possible payload. Examples of robots addressing safety through backdrivable joints (as in the WAM Arm [64.226]) or through active impedance control (as in KARES II, WAM Arm, Elumotion RT2 [64.227], DLR LWR-III [64.228]) can also be mentioned.

While a robot conventionally connotes a stand-alone system with some automation features, a smart bed and a smart home can legitimately be termed robots since they sense and act with motors under the shared control of its human users and its real-time software programming. Smart beds, such as SleepSmart measures body position and temperature, as well as trends and anomalies over the course of a night. Restlessness can be measured, and bed geometry (tilt of bed segments) and ambient conditions (light, temperature, sounds) can be adjusted according to presets and preferences [64.229].

Smart homes, such as the AwareHome domotic environment at Georgia Tech, NL-iRV, and the University of Tokyo [64.230], provide integrated climate, security, lighting, entertainment and transport assistance, which is enabling especially to persons with severe functional disabilities. Coupled with health care-related

functionality (following section), these robotic homes can allow a person with a cognitive or physical disability to control many ADL functions and live safely through monitoring.

Manipulation Aids: Wheelchair Manipulator Arm Systems

A need for electric wheelchair users is the manipulation of objects while navigating a home or a public place such as a restaurant or grocery store. The assistive robot service manipulator (ARM) (Exact Dynamics, Netherlands) – previously known as MANUS – is a commercial robot arm that can be attached to an existing wheelchair to the side of the lap tray and controlled by the wheelchair's own joystick or a number pad [64.23, 231] (Fig. 64.13). The robot has undergone numerous user studies with persons who have muscular dystrophy, a high-level SCI or CP. Worldwide, this is currently the only commercial rehabilitation robot arm that can be prescribed by a physician and that is reimbursed by a government health care system.

Weston [64.232] and Bridgit [64.233] are two wheelchair manipulator arm systems addressing the issue of interaction safety in their design, as for some of the manipulation aids with a fixed base presented earlier. Weston uses low-power motors in order to statically and intrinsically limiting the arm's acceleration, force and payload. Bridgit is a manipulator arm placed



Fig. 64.13 Wheelchair manipulator robot MANUS developed at the Rehabilitation R&D Center, Hoensbroek, and marketed by Exact Dynamics (The Netherlands)

on a wheelchair on a rail system. The robot moves over the rail system resulting in optimal positioning for each task. The rail system also allows for easy docking of the robot either on the back or front side of the wheelchair when not in use.

Manipulation Aids: Mobile Autonomous Systems

The most commonly thought-of form of a robot is that of an autonomous, mobile system with arms, having sensory-motor functionality similar to that of a human being, while serving people in performing menial physical tasks. This Handbook's chapter on Humanoid Robots explores the domain as well (Chap. 67). Since locomotion is a key requirement for Humanoid robotics, other robots with wheeled bases have been developed before the first walking robots were invented to explore more applied domains with more short-term usefulness. In film, robots such as Star Wars' R2D2 have made this form factor commonly known around the world. More recently, real robots such as the Help-Mate [64.234] have been employed in US hospitals as fetch-and-carry robot orderlies, using floor maps and short-range ultrasonic sensors for navigation and obstacle avoidance. The Italian MovAid research robot platform [64.235] (in Fig. 64.14) adds manipulation and vision to these capabilities to navigate in home-like environments to provide object manipulation and device operation to individual users. The European project Robot-Era [64.236] is following up these developments with a specific target on the needs of aging population. The German Care-O-bot [64.237] has explored advanced navigation and sensing in a wheeled robot that can also be used as a physical support to people requiring mobility and stability assistance. It has also doubled as a mobile kiosk, moving around a trade show floor and delivering information to attendees. In [64.238] a case study of a personal robot based on the PR2 Humanoid robot (Willow Garage, Menlo Park) is presented. The approach pursued consists of developing a diverse suite of open-source software tools that blend the capabilities of the user and the robot in order to enable the assistive mobile manipulators to move in real homes and work with people with disabilities.

Mobility Aids: Wheelchair Navigation Systems

A critical function for people who use electric wheelchairs for their mobility impairment and who in addition have communication or cognitive disability is semiautonomous navigation assistance (Fig. 64.15).

Add-ons to commercial wheelchairs have been developed by numerous research groups for this service. Such wheelchairs are typically referred to as smart or intelligent wheelchairs. As proposed by *Simp-*



Fig. 64.14 MovAid (after [64.239])

son [64.240], smart wheelchairs can be classified by form factor: early smart wheelchairs were mobile robots with added seats. The vast majority of smart wheelchairs developed until 2005 were based on heavily modified, commercially available, powered wheelchairs. Only a smaller fraction of them were

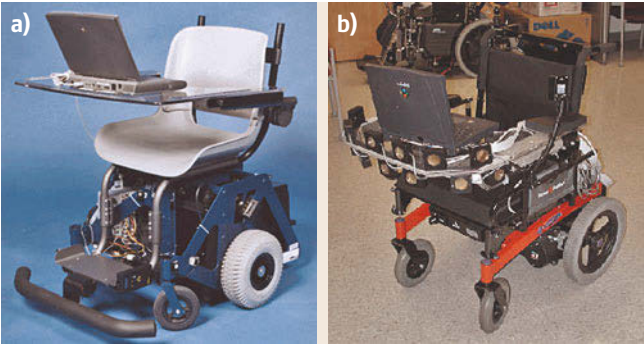


Fig.64.15a,b Wheelchair navigation aids: (a) Wheelesley and (b) Hephaestus

equipped with *add-on* units that could be attached to and removed from the underlying powered wheelchair.

The NavChair [64.241] was one of the first to demonstrate robust wall-following, door passage even with narrow doorways, and speed adaptation to people walking in front of the wheelchair, all using only short-range ultrasonic and other sensors, but not vision. The Hephaestus [64.35] is a next-generation system made specifically as a commercial accessory for a variety of wheelchair brands, tapping into the joystick controller and power system. The *Wheelseley* [64.242] and KARES [64.33] robots have explored similar functionality using a vision system for scene analysis and way-finding.

More recently, the CanWheel project team developed an intelligent wheelchair system called NOAH [64.243, 244]. The system has three main capabilities: collision avoidance, infer the user's goal location/activity and provide automated reminders, provide navigation assistance using prompts. The rationale

for proposing such solutions is to enhance mobility and to help improving the quality of life of older adults with cognitive impairments, while simultaneously reducing the burden on caregivers.

In 2013, *How* et al. [64.245] proposed a new intelligent wheelchair system (IWS) with anticollision and navigation features. User trials showed the IWS's potential to improve powered wheelchair safety and subjective usability.

The IntellWheels [64.246] project proposes a modular platform based on a multiagent system paradigm for the development of intelligent wheelchairs based on commercial products. Within this project, promising results have been achieved on the development of adapted control methods for CP users of an intelligent wheelchair. Experiments demonstrated that users felt that they had better control over the wheelchair movement when using shared control rather than manual or automatic control modalities [64.247].

The iBOT [64.248–250] is a powered wheelchair for persons with mobility impairment developed by Kamen, in a partnership between DEKA and Johnson & Johnson's Independence Technology division. Research on iBOT was discontinued in 2009. The iBOT features self-balancing technology, which allows users to go up and down staircases, to navigate on uneven terrain and to *stand* at an eye level with people walking nearby.

Mobility Aids: Walking Assistance Systems

A third type of mobile robot for stability assistance has the peculiarity that it is underactuated and has similarity with the *co-bot* concept, in that the wheels are not driven, but are actively steered and braked (Fig. 64.16). The concept of collaborative *co-bots* was originally introduced by *Colgate* et al. for robots operating in di-



Fig.64.16a–c Human assistance robots: (a) Care-O-bot, developed by the Fraunhofer Research Institute (Germany). (b) Helpmate by Transitions Research Inc., USA. (c) Pam-Aid (aka Guido), developed in the UK

rect physical interaction with a human factory worker, handling a shared payload. They are a marked departure from autonomous industrial robots, which must be isolated from people for safety reasons [64.251, 252]. Co-bots interact with people by producing software-defined *virtual surfaces* which constrain and guide the motion of the shared payload, but add little or no power [64.253]. Today, cobots are being prototyped in the rehabilitative and assistive context, e.g., for bed to chair/wheelchair transfer or table-top upper limb, stroke rehabilitation at home. For example, the Pam-Aid [64.254] looks like a closed-front walker on wheels and has bicycle-type handlebars. The person walking behind the device turns the handlebars, causing the wheels to turn in the correct direction. If the ultrasonic sensors detect an obstacle in front of it, the brakes prevent the user and device from colliding with it. The Care-O-bot (see earlier) designed originally as a mobile autonomous robot approximately human size, has a similar set of handlebars, similar to the Pam-Aid it, so it can be used as a smart walker. The larger mass of the Care-O-bot, however, requires it to be motorized.

Mobility Aids: Exoskeletons

Exoskeletons for walking assistance are similar to robots used in treadmill-based environments for rehabilitation. These systems are portable and autonomous and intended to be used in daily life scenarios. Several review papers have been recently published [64.255–257] on this topic.

In the framework of NIST's Advanced Technology Program, Ekso Bionics (Berkeley, USA) developed the Ekso device [64.258] (Fig. 64.17). This robot has been developed for people with lower extremity weakness or paralysis due to neurological disease or injury (e.g., spinal cord injuries, multiple sclerosis, Guillain-Barré syndrome) and it has an almost anthropomorphic structure with hip and knee joints actuated in the sagittal plane. The ankle joints are not actuated but are compliant in the sagittal plane and locked out in the other DOFs. Testing of the device has included paraplegic persons with complete or incomplete paralysis [64.259] and chronic stroke patients [64.260].

The ReWalk was developed by Argo Medical Technologies [64.261]. It is actuated by DC (direct current) motors at the hip and knee joints in the sagittal plane, while the ankle joint is not actuated. The system is designed with a remote controller that can be used to change the motion mode (e.g., ground walking, climbing stairs). A posture sensor on the torso detects the upper body movement of the user and estimates motion intention. The wearer also has to use crutches for stability and safety reasons. The system is undergoing

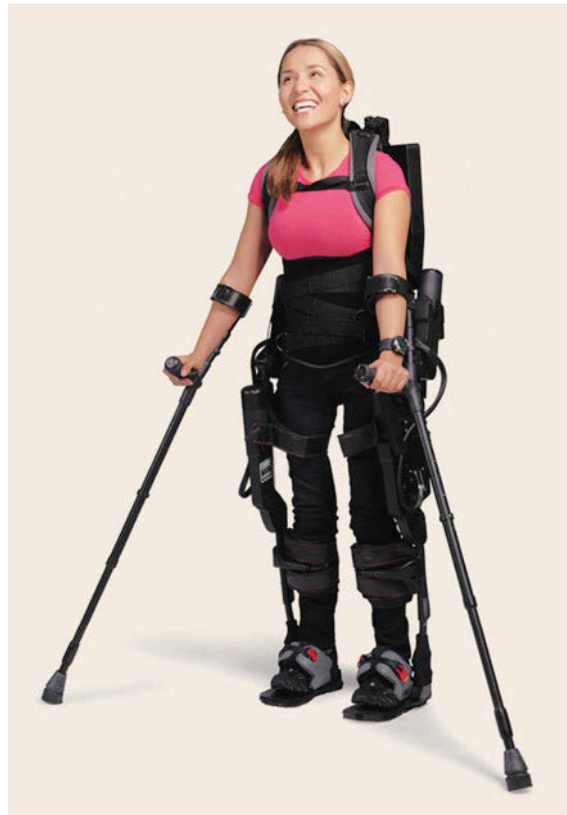


Fig. 64.17 Ekso Bionics exoskeleton for paraplegics (after [64.258])

clinical trials among other research centers at Moss-Rehab (Philadelphia, USA) and at the Centro Protesi INAIL di Vigorso di Budrio (Bologna, Italy) on paraplegic subjects. The device is now available on the market in two versions: the ReWalk-Rehabilitation for institutional use and the ReWalk-Personal developed for daily use (Fig. 64.18).

Sankai's group at the University of Tsukuba (Japan) developed an exoskeleton both for performance augmentation and for rehabilitation and assistance [64.263, 264]. The current version, HAL-5, powers the flexion/extension of hip and knee via DC motors while ankle dorsi/plantar flexion DOF is passive. The HAL-5 system (Fig. 64.19) integrates a number of sensors: skin-surface EMG electrodes placed below the hip and above the knee on both the anterior (front) and posterior (back) sides of the wearer's body, potentiometers for joints angles measurement, ground reaction force sensors, a gyroscope and accelerometer mounted on the backpack for torso posture estimation. HAL-5 is currently commercialized by the spinoff company Cyberdyne (Tsukuba, Japan). To date, it appears that no peer-reviewed, quantitative results have been published



Fig. 64.18 ReWalk computerized exoskeleton (ReWalk Robotics, Inc., USA; after [64.262])

on the effectiveness of the exoskeleton for the improvement of walking functions.

The Vanderbilt powered orthosis [64.265] is a powered lower limb exoskeleton intended to provide gait assistance to individuals suffering from spinal cord injury by providing assistive torques in the sagittal plane for both the hip and knee joints. It includes neither a portion that is worn over the shoulders, nor a portion that is worn under the shoes. Each joint is powered by a brushless DC motor. The orthotic is intended to be worn together with a standard ankle-foot orthosis, which provides support at the ankle and prevents foot drop during swing. In order to demonstrate its ability to assist walking, the orthosis was experimentally tested on paraplegic subjects. Experimental results indicate that the orthosis is capable of providing a repeatable gait with knee and hip joint amplitudes that are similar to those observed during non-SCI walking.



Fig. 64.19 Robot suit HAL-5 designed by Japanese robotics firm Cyberdyne

REX, produced by REX Bionics (Auckland, New Zealand), is an anthropomorphic lower body robot designed for sit-to-stand, stair climbing and overground walking, without the use of crutches. The system does not use sensors to detect the intention of the user but rather it uses a joystick as its interface. The system has been tested with healthy subjects, and for sit-to-stand of wheelchair users [64.266].

Cognitive Aids

There has recently been increased interest in using robots as motivational and educational agents during rehabilitation therapy. This approach typically involves small, pet-like, toy-like, approachable devices that do not physically interact with the patient, but exist primarily to engage the patient in an affective way that promotes personal health, growth, and interaction. For more information, please see Chap. 73.

64.4 Smart Prostheses and Orthoses

In 2005, the Defense Sciences Office (DSO) of the US governmental research agency DARPA launched a program to revolutionize prosthetics in a four-year timeframe. According to the agency website, this program will:

deliver a prosthetic arm for clinical trials that is far more advanced than any currently available. This device will enable many degrees of freedom for grasping and other hand functions, and will be rugged and resilient to environmental factors. In 4 years, DSO will deliver a prosthetic for clinical trials that has function almost identical to a natural limb in terms of motor control and dexterity, sensory feedback (including proprioception), weight and environmental resilience. The four-year device will be directly controlled by neural signals. The results of this program will allow upper limb amputees to have as normal a life as possible despite their severe injuries.

64.4.1 Grand Challenges and Roadblocks

This program announcement lays down the grand challenge for prosthetics research in an ambitious timeframe: develop an artificial limb that has function and durability at least as good as a natural limb. There are several roadblocks to meeting this challenge. First, providing an intuitive way for individuals to control and coordinate multiple joints of a robotic limb is challenging. Second, robots do not yet match the human arm in terms of the combination of range of force, weight, and duration of use with a portable power source. Third, human limbs are rich with tactile and movement sensors. Installing artificial sensors on a robotic limb, and then returning information from those sensors in a way that is usable by the user is challenging. Thus, solving the grand challenge will require better sensory-motor interfaces for prosthetic limbs, as well as lighter, stronger actuators, and better power sources.

Substantial progress has recently been made in improving sensory-motor interfaces for prosthetic limbs, and this progress is the focus of this section. For the current state of robotic actuators that could be used in prosthetic devices, the reader is referred to Chap. 77 on Neurorobotics. For an overview of the design of conventional prosthetic hands and arms, the reader is referred to [64.267].

64.4.2 Targeted Re-Innervation

Standard prosthetic arms and hands are commonly controlled with a cable drive or by electromyogram (EMG)

signals from residual muscles. For example, to open and close an artificial hand, one common technique is to place a Bowden cable around the shoulders in a harness, and connect the cable directly to the artificial hand. The user can then shrug the shoulders to move the cable and open and close the hand. Alternately, electrodes can be placed on a muscle in the residual limb or on the user's back, for example, and then used to control a motor on the artificial hand. The cable technique has the advantages of simplicity, and of having the property of extended physiological proprioception (EPP), which refers to the fact that the grip force is mechanically transmitted back to the user's shoulder muscle force sensors so that the user can gauge the strength of the grasp. Because of their simplicity and EPP, cable drives (or body powered prostheses) have been more popular than myoelectric (or externally powered) prostheses. However, the body-powered technique is amenable to controlling only one degree of freedom at a time, although chin switches, for example, can be used to switch between degrees of freedom in a somewhat cumbersome way. The myoelectric approach can be used to control multiple degrees of freedom, but such control is nonintuitive and cumbersome. Also, multiple control sites for reading out EMG are not available for people who have lost their entire arm. Thus, prosthetic control systems are typically limited to one or two degrees of freedom, while functional arm and hand movement benefits from at least four degrees of freedom (three to position the hand, and one to open and close it).

Kuiken et al. [64.268] recently developed a novel approach to improving control of a multijointed prosthetic arm. In this targeted re-innervation technique, they re-routed the nerves that previously innervated the lost limb to a spared muscle, and then read out the user's intent to move the limb using electromyography at the spared muscle. They demonstrated this technique in a bilateral shoulder disarticulation amputee who had lost both of his arms in an electrical power accident. They took the residual brachial plexus nerve for the left arm, which normally innervates the left elbow, wrist, and hand, and moved it to the pectoralis muscle. The subject could still contract his pectoralis muscle, but this muscle was no longer useful to him since it used to attach to his now-missing humerus. A surgeon dissected portions of the nerve associated with different muscles in the elbow, wrist, and hand, and innervated three bundles of the pectoralis muscle. After three months, the nerve re-innervated the bundles so that the patient could cause the bundles to twitch by trying to bend his missing elbow, for example. Surface EMG electrodes were

placed over the bundles. Then, when the user wished to open his hand, for example, a pectoralis muscle bundle contracted, and this contraction was detectable with the **EMG** electrodes. The **EMG** signal was in turn used to control the hand motor of the prosthetic arm. The net result was that the user could will his different (missing) anatomical joints to move, and the corresponding joints on the robotic arm would move. He could simultaneously operate two joints, such as the elbow and the hand. The user became able to do tasks that he was not able to do before with his conventional myoelectric controlled arm, such as feeding himself, shaving and throwing a ball. A secondary remarkable finding was that the sensory neurons in the re-routed nerves re-innervated sensors, so that now when the person's chest is touched, the person perceives it as a touch to his missing limb. This sensory re-innervation could possibly be made into an interface to provide tactile sensation from the artificial limb. These findings were recently confirmed in another person who received targeted re-innervation [64.269].

64.4.3 Neural Interfaces for Limb Prosthetic Devices

Neural interfaces provide an interesting and challenging solution to retrieve the natural way of interfacing the human nervous system to prosthetic artifacts. They are systems capable of recording either invasively or noninvasively the electrical activity of peripheral nerves as well as of the brain cortex. It has also recently been shown that the direct electrical stimulation of a residual peripheral nerve can provide usable information regarding force to a person with an amputation [64.270], thus paving the way for bidirectional neural interfaces capable of restoring both efferent and afferent information flow to/from the prosthesis. Recently, thin film intrafascicular electrodes implantable in peripheral nerves have been developed [64.271], and successfully validated in 2008 in Italy at Campus Bio-Medico University of Rome on a human amputee [64.272] within the LifeHand project, a cluster of European and Italian research actions focused on neural interfaces for prosthetics (Fig. 64.20). In 2013, a second round of experiments in Italy demonstrated the possibility of delivering physiologically appropriate (near-natural) sensory information to an amputee during the real-time decoding of different grasping tasks to control a dexterous hand prosthesis by stimulating the median and ulnar nerve fascicles using transversal multichannel intrafascicular electrodes, according to the information provided by the artificial sensors from a hand prosthesis [64.273]. The results also demonstrate that the subject was able to identify the stiffness and shape of

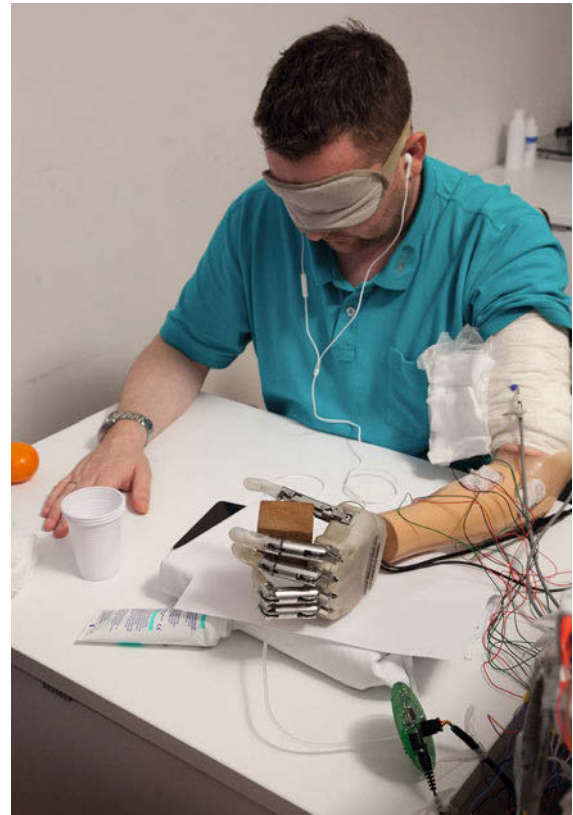


Fig. 64.20 LifeHand aims to create a completely implantable prosthesis system, richly sensorized and controlled through the patient's nervous system, with a dexterity comparable to a natural limb (courtesy of Campus Bio-Medico University Rome, Italy)

three different objects by exploiting different characteristics of the elicited tactile sensations. These results are in line with earlier studies which outlined the importance of restoring tactile feedback on a prosthetic device, such as the one proposed by *Meek et al.* in 1989 [64.274].

Today the above mentioned approach is trying to be extended on lower limb prosthetics as well. *Herr et al.* a **MIT** pioneered a new class of bio-hybrid smart prostheses and exoskeletons [64.275] aiming at improving the quality of life of people with physical challenges. Some of these devices are now commercialized by a spin-off company, BiOM. For instance, a computer-controlled prosthesis called the Rheo Knee [64.275] is outfitted with a microprocessor that continually senses the joint's position and the loads applied to the limb. A powered ankle-foot prosthesis emulates the action of a biological leg to create a natural gait, allowing amputees to walk with normal levels of speed and metabolism as if their legs were biological [64.275].

There has also recently been progress in decoding movement-related signals in real-time directly from the brain (see the cover story and related articles in *Nature* of 13 July 2006 [64.276]. The first of several recent human volunteers, a person with tetraplegia due to SCI, has received a BrainGate electrode array implant, and has been able to control the movement of a cursor on a computer screen [64.277]. Noninvasive systems operate by recording brain activity from the outside of the skull via well-known clinical noninvasive diagnostic devices [64.278] such as electro-encephalogram (EEG). Individuals have been demonstrated to be able to learn to control the amplitude of the EEG signal as a function of time, or the amplitude of specific frequency components of the EEG signal, with a moderate amount of practice (several hours to several days). The level of control is sufficient to operate a typing program on a computer, or to control the movement of a cursor to multiple targets.

In summary, given the significant progress observed in the last decade, it appears that future control systems for smart prosthetics and orthoses will have the option to rely on direct interfaces to the brain, which should allow control of multiple joints through thought alone. The initial work on both targeted re-innervation and brain-machine interfaces to the PNS or to the CNS has allowed three to 4-DOF of control in a naturalistic manner and elicitation of some sensory feedback, which is an advance over conventional prosthetic control techniques.

64.4.4 Advances in Neural Stimulation

Functional neural stimulation techniques (FNSs) seek to electrically stimulate the residual nervous system to re-animate the limbs. FNS for standing, walking, reaching, and grasping has been demonstrated, but these techniques have met with limited commercial success because of a combination of factors, including the ease of use of systems that use surface electrodes, duration of use before fatigue, risk from implantation and complexity of the associated control problems.

Two research lines are being pursued to help move the FNS field forward. The first one focuses on hardware innovation. A good example is the BION, an injectable stimulator the size of a very large grain of cooked rice [64.279], which can be inserted without surgery (using a large-gauge needle) and is robust and resistant to infections. The second research line aims at stimulating the control circuits in the nervous system rather than individual muscles. For example, it has been shown that locomotor-like movements can be eliciting in multiple muscles of the cat hind limb by stimulating regions of the spinal cord directly [64.280].

64.4.5 Embedded Intelligence

Recent robotics-related advances for prosthetic legs have included embedding microprocessors and passive braking systems into artificial knees, so that the knees can, for example, be made relatively stiff during the stance phase of gait, and free to move during the swing phase of gait [64.281]. The first microprocessor knee introduced was the Ottobock C-Leg (Germany), introduced in 1999. The C-Leg uses a servomotor to adjust valves to hydraulic pistons. The rechargeable battery lasts about 24 hours. The pattern of resistance throughout the gait cycle can be adjusted for each user. A dramatic example of the benefit of the C-Leg is the story of a man who made it down from the 70th floor of the World Trade Center on 9/11/2001 with only minor bruising to his residual stump [64.282]. Other microprocessor-controlled knees are the endolite adaptive prosthesis, which uses pneumatic and hydraulic valves, the Rheo Knee (Össür Hf, Iceland), which uses magneto-rheologic fluid to vary the knee impedance and the Intelligent Prosthesis.

The first powered knee that can generate power, rather than just dissipate energy, is currently being commercialized by Össur as the Power Knee. The system combines an electromechanical power source that will be controlled with input from sensors on the sound leg shoe. Initial reports suggest that this is the first knee that allows the user to walk up stairs with a step-over-step pattern.

64.5 Augmentation for Diagnosis and Monitoring

A critical aspect of rehabilitation is health maintenance with age-related or degenerative functional decline and after a medical intervention. In-home diagnostic equipment, devices worn on or in the body for vital signs monitoring, tele-health services, and institution-based monitoring automation are all examples of systems be-

ing developed to improve the quality of life for both persons at risk and their caregivers. Institutional systems of this nature, more properly part of the field of clinical engineering, are incorporating more robotic, networked and autonomous devices to take more accurate diagnostics, provide better information to physicians and

provide faster alerts. Key enabling technologies in this field are advanced materials and nanotechnologies.

64.5.1 Grand Challenges and Enabling Technologies

For all devices that are worn on the body, the interface must be skin compatible. A grand challenge for this field in the near-term is the better incorporation of active and sensing elements with textiles. Several prototype sensor shirts show promise, but rehabilitation will have a much richer toolset for diagnosis and monitoring with advances in this area. Nanotechnology, an enabling technology for the longer term, has the promise to miniaturize virtually everything mechatronic that is currently macroscopic. Injected devices, such as nano-robotic drug dispensers and clot-busters will aid in rehabilitation.

64.5.2 Smart Homes for Health Care Monitoring and Care

A special class of fixed-station rehabilitation robots is an automation system designed to provide a safe environment to assist and monitor a person with a disability living at home or in an institutionalized setting such as an assisted living facility or nursing home.

Smart Nursing Home Automation

An assisted living, hospice, or nursing care institutional facility will include residents who have mild to severe cognitive impairment in addition to physical disabilities. The facility may have zones to separate residents who have different levels of dependency since the architectural, monitoring and personnel needs are different. To better serve residents and guests, to optimize function and to minimize cost, only the areas for persons with high dependency have a 24 h staffed vital signs monitoring and alert capability, for example. Facility care is highly staff-intensive, though automation through diagnostic vital signs monitoring, electronic surveillance, and patient tracking continue to improve safety and efficiency. Robotics and automation are beginning to find applications in the physical tasks associated with patient care, therapy and oversight. Some examples are described below.

Examples of the State of the Art

Wandering, especially at night, is a significant problem for institutional facilities with ambulatory residents who are cognitively impaired. Simple architectural modifications include painting the hallway in front of doors black to make them look like deep holes. An automated voice system triggered by a motion detector to

say *Go back to bed* is effective, but not fool-proof, either. Resident detection systems based on ID badges with embedded RFID chips that can be sensed in a hallway work, but only if the resident is wearing it. A robotic sentry system, including mobile platforms to aid in solving this problem, especially at night, has not yet been developed.

A serious rehabilitation issue in institutionalized facilities is the transfer of residents from bed to wheelchair and other surfaces. A number of manual, electric, and robotic devices have been developed to assist the nursing staff to safely transfer residents and patients who may be significantly heavier than they are. This remains an unmet clinical need, though not for lack of innovative attempts [64.283, 284].

64.5.3 Home-Based Rehabilitation Monitoring and Therapy Systems

Numerous smart homes have been developed for non-rehabilitation as well as assistive purposes [64.285]. These systems have as their goal the safety of people with disabilities living in the home and communication with caregivers outside of the home. Caregivers can be live-in family or attendants who, even when they are not home, need to be kept informed on the status of the disabled person, as well as clinicians who need to be sent regular vital signs and other medical/therapy reports. In-home systems typically feature the same principal elements:

1. Sensors to monitor both ambient and as people- and object-specific parameters (e.g., person location, stovetop operation); actuators to modify ambient conditions (heat, lighting, sound system, etc.) and operate devices (doors, refrigerator, etc.).
2. A means to network all the sensors and actuators for uni- or bi-directional communication with the host computer. This network can be wireless (e.g., 802.11 g), wired (e.g., coaxial cable), or dependent on an existing network (e.g., signals superimposed on current carried by the electrical mains wiring or phone wiring).
3. A host computer that allows all sensor states to be displayed and actuators to be operated from one or more locations in the home by the inhabitant(s) using common computer I/O devices. Higher order functions are built upon this basic capability.
4. An external network to allow communication with the Internet via phone, cable, satellite or other means. This capability allows for remote monitoring and operation, sending of alarms and discussions with rehabilitation professionals at medical centers.

The host computer software may also have higher order features, for example timers for repetitive actuation of lights and monitoring for anomalous sensor readings (e.g., call security when the smoke detector activates, alert inhabitants with in-home alarm when stove top power is on and no pot is on the stove). More advanced features that involve multi-input and multioutput control and adaptive, predictive, context-aware operation [64.286] are areas of active research, and especially important to the rehabilitation community.

As previously mentioned in this chapter, devices for home-based robot-assisted therapy have been recently developed, and home-based therapy delivered by robotic devices is expected to have a significant growth in the short-medium term.

CBM Motus [64.126] and T-WREX, [64.287, 288], a passive exoskeleton for upper limb rehabilitation now sold by Hocoma AG as ArmeoSpring, are just two examples of systems for home-based therapy described above (Sect. 64.2.3). Another example is the Hand Mentor, which is a device which uses video games and robotics to cognitively involve the patient in his/her rehabilitation [64.289, 290]. The Hand Mentor can be used in the clinic, or taken at home and incorporated into patients' daily therapy sessions to lengthen shortened tissues, facilitate hand opening and closing, and reduce spasticity. It is mainly conceived for stroke patients' rehabilitation and is commercialized by Kinetic Muscles, Inc.

64.6 Safety, Ethics, Access and Economics

Rehabilitation robots interact closely with humans, often sharing the same workspace and sometimes physically attaching to humans, as in the case of robotic movement training devices and prosthetic limbs. Furthermore, the devices are by necessity powerful enough to manipulate the environment or the user's own limbs, which means that they are also often powerful enough to injure the user or another person nearby by colliding with them or moving their limbs inappropriately. Safety is clearly of paramount importance.

A common strategy for ensuring safety is to incorporate multiple, redundant safety features. A device can be designed to be mechanically incapable of moving itself or the user's limbs in such a way as to cause injury. Limits can be placed on the range, strength and speed of actuators so that they can accomplish the desired task but no more. Break-away attachments can be used to attach to users' limbs. Covers can protect the user from pinch points in the device. Redundant sen-

64.5.4 Wearable Monitoring Devices

One component of an automated rehabilitation environment is the subsystem that a person wears to be able to measure, analyze, and communicate physiological signals to an external computer wirelessly. Systems such as the LifeShirt (VivoMetrics, Inc., Ventura) [64.291] have been and are being developed for front-line soldiers and rescue operation personnel whose health may become imperiled when out of touch with and unable to communicate verbally with their base command. For rehabilitative purposes, for example, the Intel Proactive Health Initiative [64.292] is an example of a system that use on-person position and motion sensing to detect potentially dangerous or undesirable situations.

The use of a robot to deliver therapy already enables measuring information on the patient state by exploiting robot sensors and other wearable units, if needed [64.293]. Such capability can be exploited for patient monitoring. A recent work proposed a method for reconstructing the human arm kinematics by resorting to an inverse kinematics technique for redundant robot arms [64.294].

The most significant obstacles to the widespread adoption of these technologies in the short term are cost, false-positive alarms, inconvenience and encumbrance. Advances in micro-electronics, nanotechnologies, software algorithms, and networking capabilities will continue to drive the research and consumer acceptance of this technology sector.

sors can be included, so that if one sensor malfunctions another sensor can identify the malfunction and help safely shut down the machine. Watchdog timers can monitor the health of the control computer. Software checks can limit forces, motions, speeds, and user adjustments to control parameters, as well as check for sensor health and other dangerous situations. Control strategies can be designed so that the device is mechanically compliant, reducing the risk of forcing a limb into an undesirable configuration, or of a high-impact collision. A manual override switch can be incorporated so that the user can shutdown the system. Finally, the user can be instructed on how to safely operate the device and avoid dangerous situations. Safety ultimately depends, however, on careful and rigorous failure mode analysis and remediation by the system designers.

From a system's perspective, when all else fails actively to protect the user, it must be the design itself

that makes the robot inherently unable to injure its user. Part of the solution is in reducing the weight, rounding the surface characteristics, and making appropriate materials choices. The goal of inherent safety, however, is often at odds with high performance and adequate payload for real-life tasks. Recently, several approaches to designing personal robots – in other words – the class to which assistive rehabilitation robots belong – have sought to address both goals by dividing the two tasks of compensating for gravity (arm plus payload) and moving the payload around in space [64.295]. The solution is to provide two actuators per joint on the joints that support the arm segments and payload against gravity: one slow, gear-reduced motor and energy storing device such as a large spring or compressed air volume, and one small, backdrivable motor that provides the power needed to move objects around quickly and precisely. Most robot manipulators have approximately a 1 : 10 (or worse) payload-to-weight ratio. A system with a dual, parallel actuator system that requires only the small, fast actuator to be carried in the arm, leaving the slow energy-storage system on the base and not contributing to the inertia of the arm itself, can lead to a 1 : 1 payload-to-weight ratio more in line with a human's own arm characteristics, and thereby provides a safe yet high-performance solution. An added benefit from this type of arrangement is that the movements of the arm will tend to be more human-like, providing a measure of confidence to the user that the robot is performing properly and moving in a safe way.

Strategies for improving safety have been proposed and methods to assess safety have been developed and adapted for rehabilitation robotics [64.296, 297] based on accepted risk analysis methods. While industrial robots have benefited from ISO user safety regulations since 1992 (ISO 10218), the fundamental issue of human proximity to robots for the personal, service, and rehabilitation sectors has prevented that standard from

being applicable to rehabilitation robots. Currently, a draft of a new *safety requirements for personal care robots* standard, ISO 13482, is under development. Currently, the existing industrial standards, augmented with provisions from medical equipment standards and buttressed by engineering best practices and adherence to professional codes of ethics by designers, have guided rehabilitation robotics designers. Clearly, as products appear on the market and the expected rapid expansion of this sector happens, better regulations and standards must be developed.

Beyond safety, there are other ethical concerns that will emerge as robotics technology becomes more intelligent with advances in cognitive software, more invasive with nanotechnologies and better integrated with human systems through bioengineering advances. Ethicists and roboticists are starting to deal with these issues [64.298, 299], which to date have been the purview of only futurists and science fiction writers. Chap. 80 deals with these issues in detail.

An economic advantage has not yet been demonstrated in a decisive way for most rehabilitation robotics. For example, the therapeutic benefits conferred by robotic therapy devices, and the assistive benefits conferred by wheelchair-mounted robots relative to the devices' cost, have not yet been large enough to cause widespread adoption. Improvements in their efficacy and reductions in their cost will increase their usage. For example, a robotic therapy device that helps people learn to walk after a stroke, in a way that is decisively better than other training techniques, would become widely used very quickly. Likewise, a wheelchair-mounted robot that gives a disabled person a substantial and efficient increase in autonomy at a reasonable cost would also quickly become widely used. An example of a robotics technology that has achieved an attractive cost-benefit ratio and thus is commercially successful is the powered wheelchair.

64.7 Conclusions and Further Readings

Rehabilitation robotics is a dynamic application area because its grand challenges are at the forefront of both robotics and biology research. The ongoing major themes of the field can be summarized as the development of robotic therapy devices, smart prostheses, orthoses, functional aids and nurses that match or exceed the capabilities of their human counterparts. Rehabilitation robotics is also a highly motivating field because the technology developed will directly help people who are limited in major life activities. The field will continue to grow because of the dramatic aging of

the populations of industrialized countries that is just beginning.

The grand challenges of rehabilitation robotics are grounded in the distinguishing features of the field: functional involvement with humans, a physical user interface and behavior that is intelligent, adaptive, and safe. These characteristics require high levels of redundancy, sensory-motor capability, adaptability, and multilevel software architecture. The grand challenges therefore span the domains of electromechanical design, software design, and, due to the applied and in-

nately human-focused nature of rehabilitation robotics, all aspects of user interface design, including physical, communication, learning, emotional, and motivational factors. The first products in this field have come on the market in only the last 15 years; worldwide demographic trends will provide the force to accelerate product development in the future.

For further investigation on rehabilitation robotics, there are three major sources of published information:

1. Books on personal, service and rehabilitation robotics, such as: [64.300–302]
2. Review articles in journals and periodicals, such as [64.303–307] and
3. Articles that deal with individual topics, such as those in the reference list below, and conferences such as ICORR, RESNA, RO-MAN, BIOROB, and AAATE, which are also represented in the reference list.

Cutting-edge research will be reported on the websites of investigators at academic, government and corporate research labs, and it is recommended to start at the sites of the researchers cited in this chapter.

Video-References

-  VIDEO 499 The WREX exoskeleton
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/499>
-  VIDEO 496 MIT Manus robotic therapy robot and other robots from the MIT group
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/496>
-  VIDEO 500 MANUS assistive robot
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/500>
-  VIDEO 502 The ArmeoSpring therapy exoskeleton
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/502>
-  VIDEO 503 Lokomat
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/503>
-  VIDEO 504 Gait Trainer GT 1
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/504>
-  VIDEO 505 Kineassist
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/505>
-  VIDEO 507 Ekso
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/507>
-  VIDEO 508 ReWalk
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/508>
-  VIDEO 509 HAL
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/509>
-  VIDEO 510 Indego
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/510>
-  VIDEO 511 REX
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/511>
-  VIDEO 513 Targetted reinnervation and the DEKA arm
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/513>
-  VIDEO 515 PAM
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/515>
-  VIDEO 494 The Arm Guide
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/494>
-  VIDEO 497 ARMin plus HANDSOME robotic therapy system
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/497>
-  VIDEO 498 BONES and SUE exoskeletons for robotic therapy
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/498>
-  VIDEO 495 The MIME rehabilitation therapy robot
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/495>
-  VIDEO 568 Handsome exoskeleton
available from <http://handbookofrobotics.org/view-chapter/64/videodetails/568>

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Multimedia Contents



65. Domestic Robotics

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When the first edition of this book was published domestic robots were spoken of as a dream that was slowly becoming reality. At that time, in 2008, we looked back on more than twenty years of research and development in domestic robotics, especially in cleaning robotics. Although everybody expected cleaning to be the killer app for domestic robotics in the first half of these twenty years nothing big really happened. About ten years before the first edition of this book appeared, all of a sudden things started moving. Several small, but also some larger enterprises announced that they would soon launch domestic cleaning robots. The robotics community was anxiously awaiting these first cleaning robots and so were consumers. The big burst, however, was yet to come. The price tag of those cleaning robots was far beyond what people were willing to pay for a vacuum cleaner. It took another four years until, in 2002, a small and inexpensive device, which was not even called a cleaning robot, brought the first breakthrough: *Roomba*. Sales of the Roomba quickly passed the first million robots and increased rapidly. While for the first years after Roomba's release, the big players remained on the sidelines, possibly to revise their own designs and, in particular their business models and price tags, some other small players followed quickly and came out with their own products. We reported about these devices and their creators in the first edition. Since then the momentum in the field of domestic robotics has steadily increased. Nowadays most big appliance manufacturers have domestic cleaning robots in their portfolio. We are not only seeing more and more domestic cleaning robots and lawn mowers on the market, but we are also seeing new types of domestic robots, window cleaners, plant watering robots, tele-presence robots, domestic surveillance robots, and robotic sports devices.

Some of these new types of domestic robots are still prototypes or concept studies. Others have already crossed the threshold to becoming commercial products.

For the second edition of this chapter, we have decided to not only enumerate the devices that have emerged and survived in the past five years, but also to take a look back at how it all began, contrasting this retrospection with the burst of progress in the past five years in domestic cleaning robotics. We will not describe and discuss in detail every single cleaning robot that has seen the light of the day, but select those that are representative for the evolution of the technology as well as the market. We will also reserve some space for new types of mobile domestic robots, which will be the success stories or failures for the next edition of this chapter. Further we will look into nonmobile domestic robots, also called smart appliances, and examine their fate. Last but not least, we will look at the recent developments in the area of intelligent homes that surround and, at times, also control the mobile domestic robots and smart appliances described in the preceding sections.

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65.1 Mobile Domestic Robotics

The first mention of a domestic cleaning robot dates back to 1985. The device, nicknamed *Robby*, was developed by Hitachi starting in 1983 and officially carried the name HCR-00 (Fig. 65.1). Robby was equipped with a gyroscope to keep track of its position and a rotating sonar scanner for obstacle detection.

65.1.1 Domestic Floor Cleaning

Very similar to today’s cleaning robots described further below, Robby already mapped its environment and used the map for path planning. HRC-00 remained a prototype like its successors HRC-01 to HRC-03.

**First Generation
of Domestic Cleaning Robotics (1985–1999)**
Also in 1985, the Swedish appliance manufacturer Electrolux started the development of a concept vacuum cleaner *Stardust*. The device was equipped with eight fixed sonar sensors and one rotating sensors for obstacle detection. To maintain its orientation Stardust used

an infrared sensor that tracked an infrared light bulb mounted to the ceiling. In 1988 Stardust was presented to the public at Domotechnica in Cologne, Germany, one of the largest fairs worldwide for domestic appliances [65.1].
About five years later, between 1989 and 1991, Panasonic undertook an effort to develop a domestic cleaning robot that led to two prototypes, one of them, *Brownie*, is shown in Fig. 65.1. Brownie was a battery-powered vacuum cleaner with a diameter of 40 cm, and at 18 kg, a super heavy weight compared to today’s domestic cleaning robots. It was equipped with a gyroscope, a ring of sonar sensors, and a dust sensor. Likely, it was limitations in battery technology for driving such a heavy robot, as well as the total cost, which prevented Brownie from become anything more than a prototype.

Six more years went by before Minolta presented its *Minolta Cleaning Robot* and the first European player, Electrolux, its Robot Vacuum Cleaner, later called Trilobite, which was presented to the public in BBC’s TV show *Tomorrows World* in 1996.

The devices had already become significantly smaller and lighter in these six years. The Minolta robot had dimensions of 321 mm × 320 mm × 170 mm and weighted about 8 kg. It was powered by nickel metal hybrid battery and used sonar and tactile sensors for obstacle detection, a cliff-sensor to discover staircases, and a gyroscope to track its position and orientation. Electrolux’ robot also had a sophisticated sonar system, which let it follow contours and even return to a homing position. It already had the size and shape of later floor cleaning robots.

Five more domestic cleaning robots made their first appearance during this time, which we call the infancy of domestic cleaning robotics. Two of them only reached the proof of concept level: *AutoCleaner* from InMach Intelligent Machines – the German startup later developed low-cost navigation systems for the professional cleaning robot Robo40, which became commercially available in 2007 – and Koala from EPFL-Lami. AutoCleaner was the first domestic wet-cleaner proof of concept, which cleaned the floor using a rotating microfiber towel that was pulled through a water tank. Koala used a suction spout to reach corners. Two more robots reached at least the status of industrial prototypes, but were never commercialized: Dyson’s *DC06* and *Cye* from *Probotics*. DC06 was a unique domestic



Fig. 65.1 First generation of domestic floor cleaning robots (1985–1999)



Fig. 65.2 Second generation of domestic floor cleaning robots (2000–2008)

cleaning robot. It differed not only in terms of the announced list price of approximately US\$ 4000, but also in many other aspects: Dyson claimed that it had three onboard CPUs, more than 50 sensors for obstacle avoidance, cliff-detection, localization and more. On top of that came the unique Dual Cyclone cleaning technology. The DC06 never made it to the market. Neither did Cy. Cy was a small mobile robot that could pull and push a (semi-)regular vacuum cleaner. It was announced as the *first personal robot* which could not only vacuum the floor but also serve coffee or deliver mail. It is unclear if Cy ever delivered coffee or mail or vacuumed a real living room. It disappeared as quickly as it appeared. The last out of the nine first robots that we call first generation was the Kärcher RoboCleaner. Its successor RC3000 was amongst the first cleaning robots that had a docking station at which the robot could not only recharge its battery but also unload the dust, which it had collected. We will come back to the Kärcher RC3000 in the next section.

The first generation domestic floor cleaning robots shown in Fig. 65.1 were the ones presented to the public. However, they were by far not the only ones that were developed in the period between 1985 and 1999. By browsing over the patents in the field of cleaning robots during that period it becomes obvious that many of the big appliance and electronic device manufacturers worldwide performed research and development on domestic cleaning robots. Besides the ones mentioned above, one can find such big names as Nintendo, Mat-

sushita, Sanyo, Samsung, Honda, Procter & Gamble, Electrolux, Philips, Henkel and more. So, although only a few players dared to go public, domestic cleaning was already on the radar of many international enterprises. What kept them away from taking the next steps is not hard to guess. It was the risk of getting into a rather conservative and tight market – the cleaning business is extremely conservative – with a semimature technology carrying a price tag that looked quite differently than the one on well-established technology, such as traditional vacuum cleaners.

The Second Generation of Domestic Cleaning Robotics (2000–2008)

Figure 65.2 shows the second generation of domestic cleaning robots. What made the difference between the first and the second generation? The amount of experimentation regarding the overall design decreased, with the majority of manufacturers settling on the disc shape. The number of sensors decreased, as well as their level of sophistication. Sophisticated and expensive sensors such as sonar largely disappeared. Most designs were limited to very few, simple, and inexpensive sensors such as bumpers, simple one-dimensional range sensors, typically based on infrared (IR), and cliff sensors. This was most likely a rather painful lesson learned from the designs in the first generation. What roboticists considered the state of the art in mobile robotics: environmental sensing, map building, range sensors with high quality angular and range res-

olution, and combined localization and mapping, were far too expensive to be built into a domestic cleaning robot. Those robots had to compete with regular vacuum cleaners in a price range of a few hundred dollars. This competition imposed very harsh cost limits for the robotic components that could be built into a domestic cleaning robot: 50 to 100 USD and often less. These cost constraints had a significant impact on a very fundamental expectation of what cleaning robots should achieve: systematic coverage of the area to be cleaned. Cleaning was understood to be synonymous with covering an area with a systematic and intuitive motion while applying some type of cleaning operation. Most of the patents filed for the first generation of domestic cleaning robots mentioned above described cleaning robots that were supposed to cover their workspace in a systematic fashion.

Systematic coverage, however, is impossible without absolute positioning and without decent knowledge of the environment. The second generation of domestic cleaning robots had to provide a solution for this dilemma of systematic coverage with cheap and simple sensors, which must not cost more than several tens of dollars.

The solution to this dilemma was already proposed in some early prototypes. The idea was to waive the requirement of systematic coverage, which would also involve intuitive motion patterns, and instead produce *semisystematic* coverage and *semi-intuitive* motion patterns. This semisystematic coverage was achieved by a combination of random motion, hard-coded motion patterns such as spiral- or meander-shaped motions, which – considered alone – reflects some systematic coverage, and some other systematic and intuitive motion patterns, for example, following contours of walls or other objects in the workspace. The theory of stochastic process states that the mean squared distance of a particle that performs a random walk with respect to the origin of its motion increases proportionally with time. That implies that the particle moving in confined space will cover that space in a finite amount of time.

First-generation domestic cleaning robots like the Electrolux Robotics Vacuum Cleaner (later Trilobite) or the Kärcher Robot Cleaner (later Kärcher RC 3000) already used random motion combined with hard-coded motion patterns to achieve a certain degree of coverage. But apparently the insight that the attribute *robotic* in front of *vacuum cleaner* was not enough of a sales argument to justify a price three to five times higher than that of a regular vacuum cleaner was not so easy to digest. Some of the second-generation cleaning robots were offered for a price on the order of 1500 USD or even more. In the end these robots shared the same fate: they become shelf warmers.

This is also due to the fact that in 2002 a robot was launched which was to herald a breakthrough in domestic cleaning robotics: Roomba. Its creator, iRobot Inc., had learned the lesson that others were still struggling with: if you want to sell a domestic appliance, better sell it for a price that is known for domestic appliances. For the sake of fairness one has to mention that the traditional vacuum cleaner manufacturers had to design the robots so they matched the quality and performance level that could be expected from the brand name. They could not take the risk of making their product too poor. Therefore it easily became over specified compared to what the market required at the time. New manufacturers such as iRobot in contrast had no brand name to defend [65.1].

If it is a totally new device, which may not only cause excitement but also concerns and reservations, sell it for less and not for more. When Roomba entered the market it was sold for 199 USD. That was a price, which did not cause customers to think about whether they really needed it, whether the quality was good enough, or whether the device would get into every corner of a room or underneath every couch or bed. The creators of Roomba were also smart enough not to call it a robot. This that prevented many customers from developing wrong expectation of what robots could or should do.

The robot technology that was built into the Roomba was everything but new or revolutionary. Roomba used a suspended front-shield for contact-sensing, a low-cost infrared range-sensor for contour-following, a cliff-sensor to prevent it from falling down stair-cases, and it could detect photoelectric barriers, so-called *virtual walls*, which kept it from leaving a room or a certain part of its workspace. Roomba further used the combination of random motion and hardcoded area-covering motion patterns to achieve a certain level of coverage. All this technology was known before Roomba.

Still Roomba can be seen as a milestone not only in domestic robotics but also in robotics at large. Why is that? It was the first time in robotics history that robotics was no longer synonymous with high-tech, high-price. Roomba showed that automation of everyday service tasks, such as domestic cleaning, could be achieved with a moderate effort in terms of hardware and at a decent price, given that one accepts some graceful degradation in the overall performance. There is no such thing as a free lunch, not even in robotics and this degradation in the performance is the price to be paid. What turned Roomba into a milestone was the cost-effective design, where the limitations of low-cost hardware – in Roomba's case the sensors – were balanced out by smart heuristics for problem-solving. This

Table 65.1 Technical specification of a selection of second-generation domestic cleaning robots

					
Manufacturer	iRobot	Sharper Image	Electrolux	Kärcher	Yujin
Model	Roomba	eVac	Trilobite 2.0	RC 3000	iclebo
Drive	Differential	Differential	Differential	Differential	Differential
Sensors	Suspended front shield as contact sensor, IR range sensor, four IR cliff sensors, dust sensor	Touch sensor, cliff sensor, IR for wall-following	180° sonar sensors (1 transmitter, 8 receivers), infrared cliff sensor, magnetic stripe detector, suspended front shield as contact sensor	Suspended front shield as contact sensor, four IR cliff sensor	Main brush, side brush anti-bacterial filter
Mapping and localization	n/a	n/a	n/a	n/a	n/a
Navigation/coverage	Random motion with bang and bounce, contour following, spiral motion	Random motion with bang and bounce, spot cleaning with star pattern	Wall-following, random motion with obstacle avoidance	Random motion with bang and bounce, spot cleaning with see-saw motion pattern	Heuristic pat-terns: random, circular, zig-zag, wall following
Cleaning technology	Side brush, two counter-rotating brushes, suction pump	Rotating brushes, vacuum pump	Rotating brush, suction pump	Rotating brush, suction pump	Main brush, side brush
Run time (min)	60–90	15–45	60	20–60	150
Performance	–	–	28 m ² /h	15 m ² /h	–
Docking/recharging station	Yes	No	Yes	Yes	no
Size (Ø/h) (cm)/(cm)	35/8,25	32/14	35/13	28/10	35/9
Weight (kg)	2,7	3	5	2	4
Year of launch	2002	2004	2004	2003	2005
Price range	250 USD	100 USD	1300 EUR	1350 EUR	530 USD

design of a commercially viable product, at a price point competitive with nonrobotized solutions, turned Roomba into the first successful domestic cleaning robot, and the most frequently sold robot in the past 50 years.

In Table 65.1 we give an overview of the technical specifications of some of these second generation robots. A more complete overview is included in 065-bib43

The idea to develop and commercialize a domestic cleaning robot at a price level of 199 USD, comparable to the price of traditional domestic appliances, was very appealing to consumers. However, it was not an overly profitable business model, even if Roomba was manufactured in a low-wage country at a cost of significantly less than 100 USD. Extreme cost pressure, however, often compromises the quality of a product. So a decision to adhere to this low price of below 200 USD may also have been a decision against the quality of the prod-

uct. Today nearly a dozen models of Roomba are on the market, which differ mostly in terms of their cleaning technology and extra features. Their prices are in a range from 250 to 900 USD.

The Third Generation of Domestic Cleaning Robotics (2009–2012)

The second generation of domestic cleaning robots also provided their developers and distributors with a number of painful and partly contradictory insights:

- A domestic cleaning robot sold at a price that is significantly beyond the price of comparable non-robotic devices, runs a high risk of failing, because many customers may not be willing to pay extra money for a cleaning robot just because it is a robot.
- A domestic cleaning robot sold at the same price level as an inexpensive comparable appliance, runs a high risk of failing, because the low price may

compromise the quality and functionality of the product, and many customers may not be willing to pay even a rather low price for a product that is known to be of poor quality.

- For most customers – traditional, as well as technophiles – efficient cleaning requires systematic and efficient coverage of the workspace. A domestic cleaning robot that uses sophisticated sensors to achieve systematic and efficient coverage may easily end up with a price tag that is significantly above the price of a comparable nonrobotic device and hence runs a high risk of failure.
- A domestic cleaning robot, which refrains from using expensive sensors to achieve systematic coverage but instead uses low-cost sensors for collision avoidance, fall protection, and confinement as well as using random motion combined with some hard-coded motion patterns to achieve a certain level of coverage, runs a risk of not satisfying those customers who expect systematic cleaning and coverage.

From a developers point of view these lessons sound as if customers expect not less than to square the circle. The truth is that customers do not care about squares and circles. They expect value for money.

With the insights above one could classify potential customers of domestic cleaning robots into three categories:

- Customers who only care about the price and not so much about quality and functionality. The criterion for this class of customers was obvious: reduce the price as much as possible without ignoring that there may be a bottom line for what customers might expect in terms of quality and functionality.
- Customers who care about the price and quality, but are willing to adjust their expectations of functionality and efficiency. The criterion for such customers was to reduce the price but only to a certain extent, which does not compromise the quality of the product too much. Expectations of such customers in terms of efficiency (i.e., systematic coverage) can be compensated by auxiliary equipment such as automatic charging stations.
- Customers, who care about price, quality, and efficiency. Apparently these customers are the most demanding. None of the second-generation domestic cleaning robots has really managed to satisfy them. The criterion to serve them would be to develop a low-cost navigation system based on low-cost sensors that provides systematic coverage.

As satisfying the last group of customers, which is also likely the largest of the three groups, seemed

nearly impossible, the third generation of domestic cleaning robots have diverged somewhat. Some manufacturers have focused on products that serve the first category of customers, some serve the second group and some even made an effort to square the circle.

May they be successful in the end or not, what cannot be overlooked is the explosion of the number of manufacturers and distributors of domestic cleaning robots in the past five years. At the end of the 2012, twenty-seven years after the first mention of a domestic cleaning robot to the public, Amazon alone listed more than 131 results under the key word *robot vacuum cleaner*, with 14 manufacturers and suppliers. The business to business (B2B) portal www.made-in-china.com lists more than 71 companies for *robot vacuum cleaner* and a total of 875 products. Some of these 875 robot vacuum cleaners look surprisingly similar to the products sold over B2C platforms under very-well known brand names.

In Fig. 65.3 we show some of the products, which primarily intend to serve customers of the first category and therefore stayed under a price of 200 EUR. Figure 65.3a shows a model series of six cleaning robots made by XRobot of the Chinese manufacturer Shenzhen Silver Star Intelligent Electronics Ltd. In B2B trading these robots cost between 64 and 102 USD per piece at a minimum order of 500 pieces. Most models of this series are also sold under the brand name of European and American enterprises. Figure 65.3b shows another series of still rather cheap robotic vacuum cleaners. The attentive reader may notice that the robots in the left and the right figure are not totally unique. Some just have different names and different prices. This is not entirely unintended. It just illustrates that in domestic cleaning robotics the value creation chain is no longer limited to the developers and manufacturers, just as in every other business.

Apart from a few minor details, all robots in Fig. 65.3 use very similar, though not to say the same, technology. They use very few and very cheap (contact, cliff, sometimes dirt) sensors and random motion combined with preprogrammed motion patterns. The vacuum technology consists of a rotating brush, sometimes combined with a small fan. Not surprisingly, robotic vacuum cleaners like the ones in Fig. 65.3 are often called Roomba-clones. The collection of robots in Fig. 65.3 is neither representative nor comprehensive.

Roomba has undoubtedly written robot history. It is the merit of Roomba and its developers that domestic cleaning robots are no longer considered as gadgets but as real appliances. Roomba has opened the door for all



Fig. 65.3 Third generation of domestic floor cleaning robots: low-cost, low-tech



Fig. 65.4 The seventh generation of Roombas

the cleaning robots mentioned above, be they Roomba-clones or not. And Roomba is the by far the best-selling robot ever.

In Fig. 65.4 we show some of the grandchildren and great-grandchildren of the very first Roomba, which started in 2002. The Roomba has gone through several facelifts in these ten years. The latest series, the Roomba 700 is the sixth generation of Roombas. It has matured quite a bit in many respects. It has matured in terms of handling, cleaning technology, obstacle avoidance and navigation technology. At the same time Roomba is delivered in more than a dozen versions, ranging from 250 to 900 USD. These versions differ in the design, in the sophistication of the user interface, in the navigation and coverage strategies, and in the details of the cleaning technology.

According to iRobot more than 6 million units have been sold in the ten years of its existence. Roomba has certainly satisfied quite a number of customers. It is built with good quality, and comes with a self-charging

home base and other auxiliary equipment. What has not changed, however, is the basic strategy for covering the workspace. The sixth generation just like the first uses random motion with some precoded motion patterns and heuristics.

This raises one rather fundamental question. Will Roomba's success story continue? Will it maintain its market position? Or has Roomba possibly reached or even passed its summit? These questions will not be answered before the third edition of this book, as any statement in this direction would be pure speculation.

In any case, there are a few recent domestic cleaning robots, which demonstrate that covering a work space in a systematic fashion does not necessarily require expensive sensing, that would push the price for a domestic cleaning robot to a level which customers would not be willing to pay.

Four different key technologies enable the devices shown in Table 65.2 to localize themselves and navigate

Table 65.2 Systematic cleaning at low-cost. The information in this table was partly collected from the websites and the technical documentation of the manufactures and partly from public websites such as www.botroom.com, staubsaugerroboter-test.org, www.robotreviews.com, www.geek.com, gizmodo.com, www.engadget.com

					
Manufacturer	LG	Samsung	Neato Robotics	Iclebo	Evolution Robotics/iRobot
Distributor			Vorwerk	Philips	Dirt Devil EVO/iRobot
Model	Hom-Bot 3.0	Navibot SR 8895 Silencio	Neato XV-21	Philips FC9910/01 HomeRun/ iclebo smart	Mint 4200
CPU	32 bit	2 CPUs			ARM7
Drive	Differential	Differential	Differential	Differential	Differential
Sensors	Camera (ceiling), camera (floor), sonar & infrared for collision avoidance cliff sensors, gyroscope, acceleration	Range sensors camera, cliff sensors, collision sensors, gyro	1-D laser range finder, cliff sensor, gyroscope, acceleration,	Camera (ceiling), cliff sensor, infrared for collision detection, gyroscope,	Northstar Indoor GPS, cliff sensors, bumper, gyro
Mapping and localization	SLAM	SLAM based on ceiling pictures at 30 fps (Visionary Mapping System)	SLAM based on laser range finder (onboard Room Positioning System (RPS))	SLAM based on ceiling pictures	SLAM with Northstar, map-building
Navigation/coverage	Systematic	Systematic	Systematic	Systematic	Systematic
Cleaning technology	Brush roller, 2 side brushes	Brush roller, 2 side brushes	Bristled brush	Brush roller, 2 side brushes, micro-fiber mop	Dry or wet (or pre-moistened) microfiber cloths
Run time (min)	75	90	90	70	180
Performance	–	80 m ² /h	–	40 m ² /h	–
Docking/recharging station	Yes	Yes	Yes	Yes	No
Size (Ø/h) (cm)/(cm)	36/9	35/8	34× 34/10	35/10	31× 11/ 29
Weight (kg)	3,2	3,2	5	4	2
Year of launch	2011	2011	2012	2011	2010
Price range	US\$ 799.00 (Amazon.com)	EUR 349.00 (Amazon.de)	US\$ 350.00 (Amazon.com)	EUR 499.00 (Amazon.de)	US\$ 174.00 (Amazon.com)

in an unknown domestic workspace and systematically cover that space:

- Visual odometry, with a camera pointing to the ceiling, combined with simultaneous localization and mapping (SLAM) used by LG Homebot, Samsung Navibot SR 8xxx, iclebo smart and Philips Home-run,
- Localization, using infra read patterns projected to the ceiling, and mapping based on contact information used by Mint,
- Proprioceptive motion estimation, using inexpensive inertial measurement units (including inexpensive gyroscopes and accelerometers)

- Simultaneous localization and mapping (SLAM), using, for example a one-dimensional laser rangefinder like Neato XV-xx.

These technologies by themselves are not entirely new. As a matter of fact methods such as simultaneous localization and mapping, visual odometry, and virtual landmark based navigation are not state of the technologies form a scientific point of view.

The true achievement of the developers of the above systems, which cannot be assessed high enough, is that they managed to reduce the cost of these technologies and at the same time make them robust enough for 24/7 operation. These key technologies will be described in

more detail in Sect. 65.1.2 Enabling Technologies. A review of domestic vacuum cleaning robots and some criteria to evaluate their performance are presented in [VIDEO 727](#) and [VIDEO 729](#).

65.1.2 Domestic Window Cleaning

Window cleaning does not seem to be significantly more pleasant housework as floor cleaning. Notwithstanding, robotic window cleaners have not experienced similar attention or progress as floor cleaners. As a matter of fact, today there are only three commercial robotic window cleaners on the market, shown in Fig. 65.5. www.made-in-china.com does not even list one entry for *window cleaning robot*, although two of the three commercial products are Chinese brands. Why is that so, given the fact that domestic floor cleaning has become a billion-dollar business? The answer to this question has two parts: an economic and a technical one.

The economic one is that windows in private homes are cleaned far less often than floors. Customers may hesitate to buy expensive equipment for a task that needs to be done once a month or even less. So the market for domestic window cleaners is presumably much smaller than that for floor cleaners.

The technical one refers to the technical hurdles that have to be overcome. The technical problems that robotic window cleaners have to face are:

- Adhesion to a vertical, fragile surface, which possibly needs to be moistened in order to be cleaned, and related, the power supply necessary to produce that adhesion.
- Requirements for cleaning performance; people may tolerate if the floor is not 100% clean, but nobody would buy a window cleaner that leaves streaks on the window.

While floor cleaners do not bother about gravity and falling down unless they are near staircases or ledges, gravity is an essential problem for window-cleaning robots, and the solutions are usually not very cheap. Special mechanisms have to be designed for secure motion. Typically special tether mechanisms prevent the robots from falling. Special locomotion mechanisms have to create enough adhesion force to hold a robot attached to a flat, vertical, damageable surface such as glass and at the same time move the body up and down and sideways. These mechanisms have to be small and light and create enough adhesion forces as well as low energy and resource consumption.

The two robotic window cleaners shown in Fig. 65.6, RACOON and QUIRL, are research prototypes, which were developed by Fraunhofer Institute for

Manufacturing Engineering and Automation (IPA) in Germany. In these prototypes the adhesion problem was solved by means of suction cups. RACOON used caterpillar drives that were equipped with passive suction cups. Passive means that the system does not actively create a vacuum in the cup. Rather a small valve aerates or seals the suction cup depending on the position of the cup along the drive. Drives with passive suction cups have the advantage of moderate energy consumption. They have, however, one severe disadvantage. They tend to lose their adhesion after a while. The reason for this is the torque that acts on the center of gravity of the system. Due to this torque there is a traction force acting on the upper cups while at the same time pressure is exerted on the lower cups. Without any attractive force acting on the upper cups the adhesion there gets weaker and eventually the system falls. Therefore passive suction cups are rarely practical.

An apparent solution to this problem is the use of active suction pumps, which generate a vacuum under the upper suction cups. This solution prevents the system from falling. However, supplying the vacuum to the cups makes the system significantly more complex, heavier, and larger. Researchers at Fraunhofer IPA [65.2] have therefore invented a smart solution, which gets by with passive cups, but gets around the problem of decreasing adhesion. The solution uses a spacer at the rear of the vehicle. This spacer neutralizes the torque around the center of gravity which is typical for a systems with passive suction cups. The spacer causes a traction force which acts on the lower suction cups. This traction force creates a torque around the spacer, which counteracts the torque around the center of gravity and also causes a pressure on the upper suction cups. RACOON was presented at the Hannover Fair in 2002 and got quite some attention. But it never became a product. Neither became its successor QUIRL.

In QUIRL, the number of components, the weight, and the size of the system were significantly optimized. The main functions *cleaning*, *holding*, and *moving* were unified in one single component. QUIRL consisted of

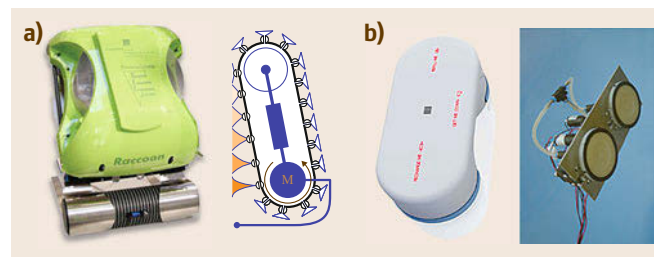


Fig. 65.6 (a) RACOON and (b) QUIRL, two early research prototypes of domestic window cleaning robots



Fig.65.5a–c Commercial robotics window cleaners (a) Windoro, (b) Winbot, (c) Hobot

two vacuum cups that were attached to a common frame which were driven by two separate motors, which rotated independently of each other. The overall motion of QUIRL could be controlled by selecting the velocities and rotational directions of the vacuum cups. If the motor of one vacuum cup was turned off and the cup did not rotate, QUIRL rotated around this fixed cup. If both motors and cups rotated in the same direction this led to an overall rotation of QUIRL about its vertical axis. If both drives rotated in the opposite direction at exactly the same velocity then QUIRL made a linear motion. If both drives rotated in the opposite direction but their velocities were not identical then the translational motion was superimposed by a rotational motion and QUIRL moved along a curved trajectory. In order to clean the surface some cleaning mechanism or tool needed to be fixed to the vacuum cups. By attaching, for example, specific cleaning towels in the cups the abrasion effect was increased and a very good cleaning performance could be achieved.

The field of robotic window cleaning has not made as much progress as domestic floor cleaning, but it has still made progress. In Fig. 65.5 we show three commercially available window cleaners – Windoro WCR I001, Winbot 7, and Hobot 168 – available today.

In 2010 the South-Korean enterprise Ilshim Global Co. Ltd. introduced its commercial window cleaner Windoro (WCR). Windoro consists of two modules, a navigator module and a cleaning module that are held together by two strong neodymium permanent magnets, whose distance can be adjusted. The navigator module and the cleaning module are placed on the inner and outer side of the window, respectively, like a sandwich with the glass pane in between. The two modules operate as a tandem. The navigator module has a differential drive system with two wide-based rubber wheels. Also the cleaning unit moves on two rubber wheels, which serve as spacers for the four spinning cleaning pads. When the navigator module moves, the cleaning module on the other side of the window moves with it. The linkage by permanent magnets obviously has one rather fundamental advantage. As long as the window does not exceed a certain thickness, namely 28 mm, the permanent magnets hold the robot safely attached

to the window. Windoro cannot fall, even if its battery runs out of power. For that reason Windoro does not need any safety mechanism like a safety rope. Unfortunately there is a price to pay for this: it is very difficult and unhandy if not impossible to use Windoro if you cannot open the window that you want to clean.

Windoro first explores the width and height of the window before it then starts to clean the window from the top to the bottom in a zig-zag motion, with a velocity of 8 cm/s. While the robot moves over the window the cleaning module sprays a cleaning solution onto the window surface. With four spinning microfiber pads the cleaning module removes dirt and sprayed solution from the surface.

The second commercial window-cleaning robot is Winbot, a product of the Chinese company Ecovacs, which has established its own brand. Winbot was first introduced in 2011. The most recent version Winbot 7 was presented at the electronics fair CES (Consumer Electronics Show) 2013 in Las Vegas. Ecovacs also manufactures and distributes the robotic vacuum cleaner family Deebot.

Winbot uses two suction rings and a vacuum pump for the adhesion at the window. The outer ring also serves as a safety mechanism. If the air pressure in the ring increases, that means Winbot has reached the edge of a window plane, it backs up, turns around and moves in a different direction. A second suction cup serves as a safety anchor for Winbot while it moves. It is connected to Winbot by a safety rope and catches the robot if it falls. Winbot can move at a velocity of approximately 15 cm/s. Its drive system consists of two differentially driven anti-slip rubber tracks.

After it has been turned on, Winbot, like Windoro, first explores the height and width of the window, then calculates a zig-zag path that covers the window area and finally executes this path. Winbot has no *active* cleaning technology such as spinning pads. It uses two micro-fiber towels that are attached to two plates at the front and at the rear of the robot. The micro-fiber towel in the front has to be moistened before Winbot starts moving. It resolves and removes the dirt. A rubber blade behind the front towel removes the remaining moisture.



Fig. 65.7 Robotics pool cleaners

The micro-fiber towel in the rear of the robot finally dries the window.

The third, and most recent, system, Hobot 168, is a product of the Taiwanese company Hobot Technology Inc. It was first presented at IFA 2012 (Internationale Funk Ausstellung) in Berlin and launched in summer 2013. It looks surprisingly similar to Quirl in Fig. 65.5 and apparently uses a similar adhesion and locomotion mechanism, namely two rotating vacuum cups, to move across the window.

The preceding paragraphs read as if the times are over where windows had to be cleaned by hand. Regrettably this is not the case. Although all three devices reasonably solved the adhesion problem their overall performance is modest. Several tests by housewives and magazines came to the same sobering conclusion: There is a lot of noise and very little cleaning. As a matter of fact, although the navigation problem on a vertical rectangular surface, which is free of obstacles apart from the window frame, seems to be a solvable one, Hobot 168 and Winbot showed a rather poor performance in terms of systematic coverage. After a semisuccessful effort to explore the width and height of the window, Winbot, in one of the tests, moved more or less erratically for several minutes, before it gave up somewhere along the road. Several of the currently available commercial window cleaning robots are reviewed in [VIDEO 734](#), [VIDEO 735](#), [VIDEO 736](#), and [VIDEO 737](#).

65.1.3 Pool Cleaning

While robotic floor cleaner and window cleaner were still struggling to get rid of the image of only being the crazy ideas of engineers and researchers at the be-

ginning of the millennium, pool-cleaning robots were already well-established products. This may be due to the fact that the challenge of cleaning a rectangular pool is rather modest and so is the *robotic technology* used in robotic pool cleaners. It may also be due to the fact that pool owners belong to a class of customers who did not create the same price pressure as the ordinary housewife.

First patents on self-propelled pool cleaning devices date back to 1965, three years after the first industrial robot was installed. Ferdinand Chauvier, a South African engineer, could possibly be considered the father of automated pool cleaning. He developed several generations of devices for pool cleaning before he finally marketed *Kreepy Krauly*, the first automated pool cleaner in 1974. Kreepy Krauly was not only the first one of its kind but also the very first domestic service robot ever, 15 years before Joe Engelberg published his book *Robots in Service* at MIT Press in 1989 and coined the term *service robot*. Since then the technology of pool cleaning robots hasn't changed much.

As one can see in Fig. 65.7, most pool cleaners have track drives, which are operated differentially. Typically the motors that drive the tracks are also connected to the front and rear scrubbing brushes, which clean the pool surface, while the robot moves. While tracked drive system were rather common for the early generations of pool cleaners, newer pool cleaners also use wheel drives, for example, the Polaris 9400 from Zodiac Pool Systems. A wheel drive can be advantageous because the space between the bottom of the robot and the ground allows a better water flow and a higher throughput. Also Zodiac claims that Polaris 9400 has higher maneuverability.

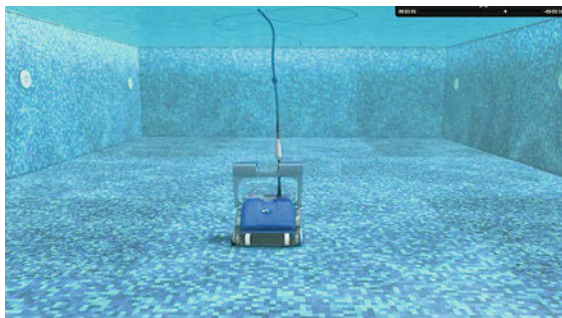


Fig. 65.8 Example of the navigation and cleaning strategy of a robotic pool cleaner

Since most sensors, which are used in mobile robots or in aerial robots do not work under water, the sensor modalities that are used by pool cleaners are manageable. Unfortunately the manufacturers do not disclose much about the sensor technology and technology in general used in their system. So we need to speculate a bit about how the behaviors shown in the commercials are internally implemented.

Most pool cleaners claim to be capable of avoiding obstacles. When they sense a collision, the back up for a certain distance, reverse the direction of motion and then continue, possibly on a track parallel to the one that led to the obstacle. They can *recognize* the walls of a pool, which form the borders of their workspace. They can even climb up the walls of a pool, float along the perimeter and then submerge again. They can *explore* the length and width of a pool. They can drive a certain distance before they change direction.

All these behaviors require a combination of several of the following sensors: *odometry* to measure traveled distance, an *inclinometer* to sense if the robot starts moving upward, e.g., when it keeps pushing against a wall and the front wheels start moving in a vertical direction, *contact sensors* to detect when the robot collides with an obstacle – be it a wall of the pool or a real obstacle on the ground of the pool – *sensor to measure the motor current*, which can be used in addition or instead of a collision sensor to detect if the robot pushes against an object, and possibly an *inertial measurement unit* to correct the heading when driving. Polaris and possibly other systems as well use an accelerometer to constantly determine its position in the pool. A sensor modality, which might be used underwater for obstacle detection and avoidance is laser, with wavelengths in the lower nano-meter range (e.g., 405 nm blue laser). But it is unknown if this principle has been considered for pool-cleaners.

In terms of *navigation and coverage* pool cleaners follow similar strategies to those floor cleaners, which we roughly classified as Roomba-clones. Earlier pool

cleaners used random motion pattern. The newer ones shown in Fig. 65.7 use certain heuristics and strategies to perform some form of localization and exploration of the pool. The Maytronic's Dolphin, for example, first explores the length and the width of a pool. After being dropped into the pool and floating to the bottom of the floor it crosses the pool until it hits the first wall. With the support of a thruster it climbs up the wall until it reaches the surface. There it hovers to the side before it submerges again and moves back to the ground of the pool. Next it moves to the opposite side of the pool, climbs up the wall, hovers to the side and glides back to the ground. While moving on the ground from one wall to the other Dolphin measures the distance from wall to wall. Once it glides back from the second wall it moves halfway back toward the other wall. It then makes a 90° turn and repeats the exploration for the second set of opposite walls. After the exploration is completed, Dolphin knows the length and width of the pool and plans a pattern of parallel and orthogonal tracks as shown in Fig. 65.8 that in the end covers the entire pool.

Removing dirt and debris from the ground and the walls of a pool, requires loosening the dirt – if it is not loose already – and to soak it into a container, otherwise the dirt would only be circulated in the pool. The container is typically a jet pipe with a filter at one end that holds the dirt back while the water flows through the pipe back into the pool. Soaking in water and debris from the floor into a filter and pumping it back into the pool requires significant suction power. This is the reason why pool cleaners typically have an external power supply. This motor serves as a pump and as a thruster at the same time. Both effects together allow pool cleaners to easily climb up vertical walls. Using inflation at the bottom of the robot, and a water jet ejected at the top, enough traction power is created that both tracked and wheeled pool cleaners can drive up vertical surfaces.

As mentioned earlier, the cleaning technology, besides the water pump and the filter to keep back the debris, consists of a system of counter-rotating rubber brushes which brush the debris underneath the pool cleaner, where it ends up in the intake socket of the water pump. [VIDEO 739](#) and [VIDEO 740](#) compare a selection of home pool cleaning robots.

65.1.4 Lawn Mowing

Together with robotic pool cleaners and domestic floor cleaners, robotic lawnmowers today count as regular everyday products. People no longer consider them mystical pieces of technology, which have their own life and which at times become so autonomous that the user no longer knows what they are after.

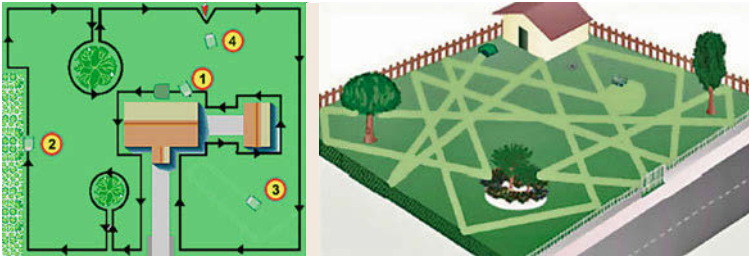


Fig. 65.9 Example for virtual fence and coverage strategy (random motion) of robotics lawnmowers

It is not surprising that robotic lawnmowers have a lot in common with domestic floor cleaners. They have to cover a workspace of a certain size with as little interaction with the owner as possible. They have to perform a certain operation to the surface such as cleaning the floor or mowing the lawn. They must not collide with any obstacles and if they do, they should at least not cause any damage. They must not get stuck anywhere in the environment and they should not leave the workspace without authorization.

The challenge for lawnmowers, much the same for domestic floor cleaners, is the systematic coverage of the workspace, which in turn requires precise positioning and mapping of the workspace. Given the fact that the price pressure is not as back-breaking as for robotic floor cleaners – there are not that many robotic lawnmowers which costs less than 1000 EUR – why not invest a little more in sensing and especially in position sensing and obtain a decent solution for the localization and coverage problem?

The answer to this question is: things are not that simple. Lawnmowers operate outdoors and none of the solution developed for the floor-cleaners in Fig. 65.2 will work. Regular **GPS** (global positioning system) has an accuracy of several meters and has a tendency to deliver erratic readings, which would lead to equally erratic motions of the lawnmowers. As a matter of fact Automower 220 from Husquana uses **GPS**, but only as an antitheft protection device. Differential **GPS**, which would provide accuracy below one meter, would be too expensive for an affordable robotics lawnmower. In a nutshell, absolute positioning or **SLAM**, which would be necessary to cover a large outdoor area like a garden in a systematic fashion, is not practical.

In order to cover their workspace robotics lawnmowers use similar strategies to the Roomba-like floor cleaners. They refer to heuristics, which do not provide an optimal performance but still show a decent result. Using sensors such as gyroscopes, digital compasses, or inertial measurement units, robotic lawnmowers follow a certain heading and cover the workspace as much as possible by parallel tracks. They move along a straight line until they hit an obstacle or reach the border of the workspace. There they back up to become clear

from the obstacle, make a U-turn by 180° and drive back the way they came. Another heuristic that is frequently applied by robotic lawnmowers is the random motion shown also in Fig. 65.9. The mower moves along a straight line until it hits an obstacle or reaches the border of the workspace but then it does not just reverse but chooses a new direction randomly.

Since robotic lawnmowers move in open space, there is a danger that they leave their workspace and travel to areas where they are not supposed to be. For floor cleaners so-called virtual walls or fences solve this problem. Virtual walls are realized by infra red light beams emitted by some projectors, which can be placed in the workspace. The robots can sense these infrared light beams and consider them as obstacles, which evoke the typical obstacle avoidance behaviors. Lawnmowers use a similar technique, which is based on induction rather than light. To mark the border of the robot's workspace the owner has to place a wire around the area, which the robot must not leave (Fig. 65.9). This wire is connected to a low-voltage alternating current source. When the robot approaches the wire an inductivity sensor senses the current in the wire and causes the robot to reverse. Today most lawn mowers use a more sophisticated so-called *true in/out systems*, where the position is permanently tracked, not only when the robot approaches or passes the virtual fence [65.3].

The very first robotic lawnmowers had to be recharged manually. To avoid an all too frequent involvement of the human into the operation, Husqvarna – one of the pioneers in robotic lawn mowing – equipped its first mower with solar panels and called it *SolarMower*. SolarMower was released in 1995, and was one of the first robotics lawnmowers. Nowadays, all lawnmowers come with a base station where they can recharge their batteries without human intervention. Also solar panels are coming back as power source, however only as auxiliary power to increase the performance and runtime between two charges and not as main power supply.

Given the fact, that robotic lawnmowers do have poor positioning capabilities, it is somewhat tricky to guide them back to the docking station once the battery



Fig. 65.10 Robotic lawnmower

gets low and needs to be recharged. Some of the lawnmowers shown in Fig. 65.10 use special wires which radiate from the position of the docking station. This way a robot only needs to follow such a radiating wire to return to the docking station on the fastest way. Another strategy is to follow the wire at the workspace border. That will eventually lead the robot back to the docking station.

An exception is the Bosch Indego, which is equipped with mapping and localization capabilities. This allows Indego to plan a path that leads to a point close to the docking station. Then the robot can follow a wire for the docking maneuver [65.1].

To comply with the safety regulations and to avoid any injuries of humans or animals the cutting mechanism has to be very lightweight and designed such that it is guaranteed to stop if the device tilts or is lifted. The cutting mechanism of robotic lawnmowers typically consists of a rotating disc with three razor-like blades, which automatically retract into their mountings if the robot is stopped unscheduled, for example, if it hits an obstacle or is lifted.

Naturally the lightweight design limits the thickness of the grass that can be cut. Also it is important for the proper functioning of robotic lawnmowers that the lawn, which is to be cut, is not too high. This in turn requires a rather regular if not continuous operation of the lawnmowers. With regular use of the lawnmowers the grass cuttings are short enough to quickly decompose into nutritious compost, so there is no need to remove the cuttings after the lawn is mowed.

Figure 65.10 shows some of the better-known robotic lawnmowers on the market today. Besides the pioneers in robotic lawn mowing Husqvarna, Friendly Robotics and Zucchetti also a number of new players have entered the market, most noticeably the German automotive supplier Bosch and the Japanese car manufacturer Honda, which has set a milestone in non-industrial robotics with its humanoid robot Asimo.

We certainly do not claim that the collection in Fig. 65.10 is complete. Like for domestic floor cleaning, Chinese B2B portals such as www.made-in-china.com or www.alibaba.com list around a hundred products under the category of robotic lawnmowers and 35 suppliers; the market development for robotic lawnmowers in the past five years was not quite as overwhelming as for domestic floor cleaners but was still remarkable. In Table 65.3 we show the technical specifications of a selection of lawnmowers from Fig. 65.10.

65.1.5 Sports Robotics

A subdomain of domestic robotics that was not included in the first edition of this handbook, because it virtually did not exist, or it was not visible at that time, is *sports robotics*. What is a sports robot? Since an official definition of this term does not yet exist – at least we haven't found one – we take the liberty and provide such a definition here. We define a sports robot as a *robotic device*, which either *supports* the human user in their physical exercises as a *coach* or a *companion*, or acts as an opponent in a game. An important aspect of this definition is the physical exercise of the human, which is supported or challenged.

We would like to emphasize that the above definition does not include any form of entertainment robots, which play games such as soccer against each other but do not involve any human activity other than watching.

In Fig. 65.11 we show three examples of *robotic baseball players*. As the name says the *Headless Batman* can act as a batter at least for exercising. It rather successfully hits baseballs thrown at it in many ways. The kinematic structure consists of *two arms, one leg and no head*, as its developer, an industrial designer from Robocross, likes to call it, and is made from auto parts, steel pipes, and pneumatic hoses. The pneumatic hoses are parts of its pneumatic actuation by an air

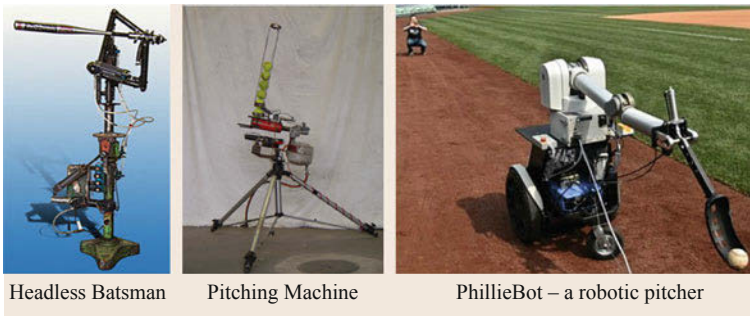


Fig. 65.11 Robotic baseball players

Table 65.3 Technical specification of a selection of robotic lawnmowers

					
Manufacturer	Husqvarna	Friendly Robotics	Zuchetti	Bosch	Honda
Model	Automower 220 AC	Robomow RL1000	Ambrogio	Indego	Miimo
CPU				ARM9 (32 bit) + PowerPC (32 bit)	
Drive	Differential	Differential	Differential 4 driving wheels	Differential	Differential
Sensors	Lift sensor collision/contact sensor	Rain sensor, lift sensor, collision/contact sensor	Grass sensors, safety sensors on handles, lift sensor, sensor for collision sensor and rollover	Lift sensor, collision/contact sensor, gyro, tilt sensor	3 × 360 degree bump sensors, 2 lift sensors
Navigation/coverage	Random	Random		Logicut navigation system: parallel tracks in parcels; localization, mapping, path planning	Random, parallel or mixed
Cutting technology	3 pivoting razor blades	3 razor blades	Rotating disc	3 pivoting blades	3 blades, which bend on hitting hard objects
Virtual fence and guides	Dual guide wires to return to the base station	Boundary wire	Boundary wire	Boundary wire	Boundary wire
Performance (m ²)	1800 (m ²)	2000 (m ²)	400 (m ²)	1000 (m ²)	3000 (m ²)
Ground speed			18 m/min	27 m/min	
Motor power (W)		3 × 150		2 × 20 + 80	2 × 25 + 56
Battery type and capacity	NiMH 30 W		Li-Ion, 6.9Ah	32 V Li-Ion, 3Ah	Li-Ion
Run time	45 min	2 h 30 min	3 h 30 min	50 min	
Docking/recharging station	Automatic docking and recharging		No	Automatic docking and recharging	Automatic docking and recharging
Theft protection	Pin code lock	Personal password		Alarm & Pin code	Pin code lock
Size (L×W×H)	71 × 55 × 30	87,5 × 65 × 31			
Weight (kg)	10	25	7,9	11.1	
Year of launch				2012	
Price range	~\$ 2400,00	\$ 1900,00		~\$ 1850,00	~\$ 2600,00

compressor. The *Headless Batsman* is fully controlled by a human operator via a remote control, which has

three buttons: one to control the robot's hip, a second one that actuates the arms and a third one to lift

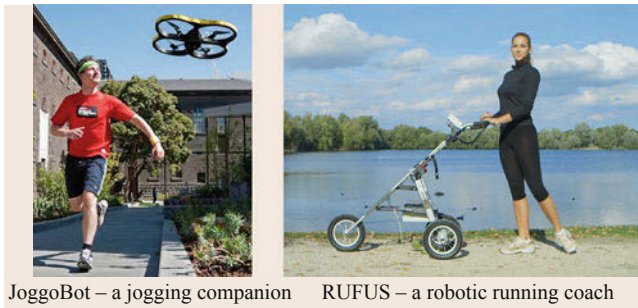


Fig. 65.12 (a) JoggoBot and (b) RUFUS two robotic sports companions

and drop the inside shoulder, changing the trajectory of its swing. Similar mechanisms like *Headless Batsman* were developed at Hiroshima University and Tokyo University.

The counterpart of *Headless Batsman* is a pitching machine, which is operated with the same remote control. The barrel of the machine is sawn-off fire extinguisher whose other end is directly connected to a one-inch port poppet valve, which in turn is connected to an 8 bar air pressure tank. The air pressure tank is supplied from a screw compressor. The charging mechanism consists of a double rod actuator with a ring welded horizontally on to the end. Mounted above the ring is a magazine that holds up to 10 balls, which directly drop into the ring. For a pitch the actuator moves the ring with the ball over the edge of the barrel, where it falls on to a small guide. From there the balls rolls backward into the barrel. The actuated ring is covered by a steel strip, which holds back the other balls in the magazine until the actuated ring returns to its initial position. Since both mechanisms are remotely controlled, the human, who controls them, can actually sit in a chair next to the playground and let the robots play against each other. Such a use would clearly violate the above definition of a sports robot but does not seem to be the one that is primarily intended.

Another robot that can throw baseballs is Philliebot (VIDEO 748) developed in University of Pennsylvania's GRASP laboratory. Philliebot was developed in a couple of weeks using only spare parts in the GRASP lab. It uses a Segway as mobile base, a Barret arm, and pneumatically actuated wrist to create the necessary dynamics for the pitch. When the button is pressed the arm moves to the back of the robot and then accelerates its motion toward the target of its pitch. When the arm reaches the highest point of motion the pneumatic wrist cylinder delivers a burst of compressed carbon dioxide to snap the wrist forward and release the ball. What remains is the question of why use robotic equipment worth several tens of thousands of dollars to throw

a baseball, given that pitching machines have existed for many years. According to the developers, the fact that Philliebot is mobile and its software can be tweaked to vary pitch velocity and trajectory was enough to justify the experimentation.

The two sports robots shown in Fig. 65.12 do not really seduce their users to sit in a chair and relax. They both serve as so-called *robotic running coaches* or *running companions*.

Researchers at the Royal Melbourne Institute of Technology in Australia have redesigned a commercially available Parrot AR Drone quadcopter and turned it into an autonomous, flying running partner for joggers, called JoggoBot [65.4]. JoggoBot uses an integrated, front-mounted camera to detect and track a special patten printed on the T-shirt worn by the jogger. JoggoBot takes off when the camera registers the pattern and rises to about the same height as the pattern on the t-shirt. An internal sensor determines JoggoBot's altitude. JoggoBot can be set into a *companion mode*, in which it flies at a steady pace at a relative distance of about three meters to the jogger or in a *coach mode* in which it flies at a slightly more challenging speed.

There are two features of JoggoBot that make the device somewhat limited: first the capacity of the battery limits the flight time to 20 min, which in turns limits the time for exercise; for a short run, this is certainly ok, but for serious training this is insufficient. Second, JoggoBot can only fly in a straight line, to let JoggoBot follow an arbitrary path the jogger needs to remotely control JoggoBot's flight path.

A slightly different concept of a jogging companion is pursued in RUFUS (VIDEO 747), which is developed by runfun (www.runfun.com), a German startup company. RUFUS is an electrically driven, automatically guided, ground vehicle that supports and guides a runner during his/her training. RUFUS plays the role of a *personal running coach*. It fulfills a similar function to a treadmill, which exposes its user to a varying strain by varying its velocity and inclination and thereby improves the fitness, endurance, and resilience of the cardio-vascular system of the user. Unlike a treadmill, RUFUS is not a stationary device, however. It drives ahead of the runner like a pace maker in a marathon or a fake rabbit in a dog race, and sets the runner's speed. RUFUS's velocity is set either manually or automatically via a training program.

If operated in *manual mode* the velocity is either set directly as a velocity set point or indirectly as a heart-beat set point. If the training guidance is based on the heartbeat, then RUFUS controls its velocity such that the runner exercises optimally and continuously within a certain heartbeat interval under a moderate stain of the cardiovascular system.



Fig. 65.13 Tele-presence robots and robotic avatars

This has a twofold use: on the one hand this prevents users from overstressing themselves through overambitious and intensive training modules, possibly from even injuring him or herself. Such a protection function is beneficial for unfit or untrained runners. On the other hand RUFUS facilitates optimal training effect and progress through a careful guidance of the training.

The training effect can be further improved if RUFUS is operated in the *program mode* instead of the manual mode. In this mode RUFUS executes complete training modules, for example pyramid speed interval workouts, which are customized to the user. Such training modules are typically elaborated on by physiotherapists or sports physicians. They can be downloaded to the RUFUS embedded PC like an app from an app store.

RUFUS has a major advantage over JoggoBot. It has a battery capacity that allows it driving for about six hours on a flat road without recharging.

65.1.6 Tele-Presence

In a world in which not only large, but even small and medium-sized enterprises operate globally, in which families are scattered over continents, in which ubiquitous presence seems to become an essential requirement for professional progress, and in which professional services are more and more delivered over the internet,

tele-presence has become a fast growing market in the past years.

Robotics adds a very important aspect to plain *tele-vision* by turning it into *tele-presence*: embodiment and remotely controlled motion. As tele-presence is nothing but the combination of tele-vision and tele-operation using a robotic device, which are often called *tele-presence robots* or *robotic avatars*.

Tele-presence robots offer a whole spectrum of services and applications ranging from plain mobile video-conferencing systems to tele-surveillance, tele-diagnosing, and tele-care, to tele-teaching and tele-commuting. The term *tele-commuting* was coined by Scott Hassan, a Google developer of the early days, nowadays entrepreneur and investor, and founder of WillowGarage and Suitable Technologies, the manufacturer of Beam-RPD (see also Table 65.4).

A *tele-presence robot* typically consists of a mobile robotic platform that:

- Can be tele-operated through some user-interface,
- Carries a camera, which often can be actuated separately (via a pan-tilt unit) and allow the operator to actively explore the remote environment, and
- Carries a display, which allows those at the remote site to see the operator of the tele-presence system and communicate and interact with it.

Figure 65.13 shows a collection of such tele-presence robots. The devices range from a price of

Table 65.4 Technical specification of a selection of tele-presence robots

				
Manufacturer	Double Robotics	Vgo Communications	Gostai	Suitable Technologies
Model	Double	VGo	Jazz Connect	Beam RPD
Height	120–150 cm	120 cm	100.5 cm	5 feet, 2 inch
Weight	7 kg	9 kg	8 kg	45 kg
Screen size	9, 7'' (iPad)	6''	5''	17''
Camera/field of view			High resolution/ wide angle, up to 640 × 480 pixels at 25 fps	Two wide-angle HD cameras
Video conferencing	Open-tok	VGo video conf.	2-way audio and video for remote discussions	–
Network	WiFi	WiFi / 4G / LTE	WiFi	WiFi (two dual-band radios) / 4G
Remote Control	iPad App	VGo App	Intuitive control interface on internet browser	Beam software client, mouse, keyboard, or Xbox controller
Navigation	Tele-operated	Tele-operated	Tele-operated with obstacle detection	Tele-operated
Sensors	Gyroscope, accelerometer	Obstacle and cliff detection sensors	12 ultrasonic sensors, 4 IR receivers (for base docking), telemetric laser for autonomous navigation	–
Drive	Differential (10'' wheels)	Differential	Differential	Differential
Battery	Lithium ion	–	–	–
Run time (h)	8	12	5	8
Docking station	–	Yes auto-docking	Yes auto-docking	Yes

some US\$ 1500 for TeleMe from MantaroBot to more than ten-fold that amount for Beam RPD from Suitable Technologies. The system [RP-VITA](#) (Remote Presence Virtual + Independent Telemedicine Assistant) emerging from a cooperation between InTouch Health and iRobot is available only for lease, at a monthly fee of \$ 4700. Giraff is the result of a European research project lead by Giraff Technologies funded by the European Commission and is not commercially available yet.

Not all tele-presence systems shown in Fig. 65.13 can be classified as domestic robots. A system that clearly stands out and is by no means a domestic robot is [RP-VITA](#) by InTouch Health and iRobot. [RP-VITA](#) is a remote healthcare system. [RP-VITA](#) shall enable doctors to command any clinical, patient or care team management process remotely. [RP-VITA](#) has a full-fledged autonomous navigation system that allows the personnel to focus on the patient care task rather than on remote navigation. This feature has been awarded clearance by the US Food and Drug Association (FDA).

[RP-VITA](#) further provides access to important clinical data to support physicians, nurses and other care personnel in their diagnosis and other medical workflow. For example [RP-VITA](#) connects with diagnostic devices such as ultrasound and comes equipped with the latest electronic stethoscope. So [RP-VITA](#) is in a class of its own, which may also justify the higher price.

Apart from [RP-VITA](#), the tele-presence robots shown in Fig. 65.13, can all be classified as semiprofessional or domestic service robots. The functionalities and services they offer do not necessarily vary on the same scale as their prices. This can be seen by a comparison of two of the above systems: Double and Beam RPD (see also Table 65.4).

Double is not much more than a mobile iPad equipped with the video-conferencing system Opentok. The mobile base uses a Segway-like dual-wheeled drive system that can balance a pole, which holds the iPad. When Double stands still, two retractable kickstands are deployed and allow the system to put the control system in an idle mode and save energy. Double can

be remotely controlled and driven around a remote site through an app installed on a second iPad that enables communication with all known Doubles over the web. The height of the iPad holder can be remotely adjusted to enable communication at eye-level. Double Robotics list a number of potential services and applications for which Double could be used: Companies with sites at various locations can use Double to improve communication and collaboration between remote teams. Families can use Double to communicate with family members living abroad. Museums and art galleries can use Doubles to offer remote tours through their exhibitions.

Beam RPD uses two HD cameras with custom wide-angle lenses instead of the plain iPad camera. This gives Beam RPD peripheral vision that is comparable to a human's field of view. A digital zoom lets the op-

erator further focus on details in the remote site. Beam uses an array of six microphones and audio processing algorithms, background noise reduction and echo cancellation. This equipment gives Beam an audio-quality, which obviously goes far beyond that of an iPad. Beam uses a 17-inch screen mounted at a height of 1.58 m that allows the display of a human face at its natural size and height. Another feature that goes beyond iPad standards is the WiFi connectivity. To provide reliable and seamless WiFi connectivity, Beam uses two dual-band radios and proprietary roaming algorithms. Altogether it is obvious that Beam RPD is far more than a movable iPad. It is left to the customers to decide whether this is worth a price which is an order of magnitude higher.  VIDEO 741,  VIDEO 742,  VIDEO 744, and  VIDEO 745 introduce several of the tele-presence robots available on the market today.

65.2 Enabling Technologies

The mass consumer market is very price-sensitive, so the price of the robot is key for the success of the product among consumers. Certain guidelines used in the consumer electronics market are relevant for the domestic robot market to provide a rough estimate of cost of the robot. Let's say that you want to develop a floor-care robot that would retail at \$ 300, the *rule of thumb* is that your bill of materials (BOM) should be between 1/3–1/5 of the retail price. In other words, your BOM should be within \$ 60–\$ 100! And the BOM must include all mechanical parts, electrical parts, battery, processor, memory, motors, assembly, packaging, user manuals, etc.

Given the extreme cost constraints outlined above, this chapter focuses on enabling technologies that are viable, from the cost point of view, to be included in a mobile domestic robot with a price lower than \$ 1000 (or ideally below \$ 500). These technologies are required to have a reliability level in line with the expected life time (and warranty) of the product; otherwise, no matter how good the technology is, if it stops working in an unreasonable period of time, the robot will be returned to the retailer. Special emphasis should be placed in the ease of manufacture of the technology. Difficult to manufacture components create delays in the production line, decreasing the yield of the product and eventually increasing the overall cost of production, leading to either eroding profit margins or a rise in the retail price.

Mobile robots need to sense and understand the environment in which they operate. The first key enabler is the capability of detecting obstacles and hazards

to safely and accurately navigate around them. Section 65.2.1 describes the different available technologies for obstacle and hazard detection. The second key enabler is the ability to localize and create a map of the environment to intelligently plan actions and motions that allow the robot achieve its goal. Section 65.2.2 presents the technologies available for localization and mapping using a number of low-cost, yet powerful sensors. Section 65.2.3 discusses alternative approaches to coverage of the space implemented in commercial products.

65.2.1 Sensing and Obstacle Avoidance

Domestic robots aim to take care of tedious chores, interacting with a household that includes owners, children, babies, pets, and stationary objects such as chairs, tables, walls, etc. Domestic robots must be safe in order to gain acceptance in our daily life: it is not tolerable to have a robot falling down the stairs or hurting a household member. Thus, robots must be equipped with drop/cliff sensors and proximity sensors that ensure proper operation while still satisfying the mentioned cost constraints.

Cliff Sensors

A number of solutions are present in current robots in the market. Off-the-shelf solutions are IR sensors from Sharp that consists of an emitter (light emitting diode LED) and a receiver (photodetector or position-sensitive-device PSD) that provides an output proportional to the distance to the object. The Roomba uses

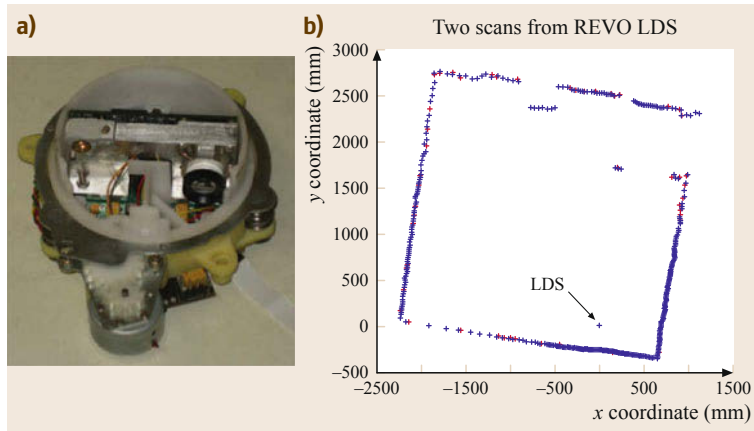


Fig. 65.14a,b Laser Distance Sensor. (a) Prototype and (b) occupancy map generated with the sensor

a custom [IR](#) cliff sensor based on a similar principle that trades generic distance measurement with sensor cost. The Mint robot from Evolution Robotics employs a factory-calibrated mechanical hammer that triggers upon cliff detection. Solid-state sensors are usually more reliable than mechanical sensors, since they do not have moving parts, but have the drawback of a response dependent on the reflectivity of the surface in the [IR](#) spectrum and a dead-band in the response.

Contact and Proximity Sensors

Mechanical switches, called *bump sensors*, are commonly used for detecting when the robot gets in contact with obstacles. Bump sensors are cost-effective solutions providing the ability to stop the robot without damaging the obstacle. Touching obstacles is not desired unless performed very gently to ensure that the robot goes under curtains and bed skirts. [IR](#) and sonar sensors are frequently employed as touchless alternatives to the bump sensors by measuring the distance to obstacles. Both types of sensors are composed of an emitter and a receptor with an output proportional to the measured distance. [IR](#) sensors are usually more focused than sonars and less sensitive to multiple reflections on walls and other obstacles, but might lose thin obstacles such as chair legs. This type of sensors provides a point-wise measurement of distance to obstacles, so a robot needs a number of these sensors to obtain a dense representation of the obstacles in the environment. The information on obstacles and hazards (cliffs) is collected in occupancy grid maps and used for decision-making in systematic cleaning robots. A number of cost-effective dense distance measuring sensors have recently appeared in the market and will be discussed in the next sections. These dense distance measuring sensors have a cost on the order of tens of dollars, while the point distance measuring sensors have cost only a few dollars, so most of the domestic

robots currently available on the market have yet to incorporate dense distance measuring sensors. The only exception is the Neato XV-21 that uses a low-cost laser distance measuring system.

Laser Distance Sensor

A low-cost Laser Distance Sensor was developed by Konolige and colleagues [65.5] using a laser point beam and a global shutter [CMOS](#) imaging sensor separated by a small baseline. The system operates by triangulation and achieves full 360 planar scan by rotating the optical assembly on a full circle. The sensor has a range of 0.2 to 6 m with an error < 3 cm at 6 m and an angular resolution of 1 degree, providing 4000 readings per second (up to 10 Hz) with a small size (approximate width of 10 cm shown in Fig. 65.14a) and low power (< 2 W). The sensor is eye safe and provides measurements that enable laser-based [SLAM](#) as shown by Fig. 65.14b.

Structured-Light Distance Sensors

Structured-light distance sensors consist of an emitter that projects a known pattern on the environment and a receptor that computes depth based on the deformation of the received pattern. The Kinect [65.6] interface to the Xbox game system uses a structured-light sensor from PrimeSense [65.7] thus showcasing the readiness of this sensor for consumer applications. The emitter consists of a laser with optics that projects a known pattern (Speckles [65.8, 9]) in near-[IR](#) light and a complementary metal-oxide-semiconductor ([CMOS](#)) [IR](#) camera that observes the pattern to estimate depth using triangulation. The emitter and the camera are calibrated during manufacturing assuming a rigid configuration. The speckles can be further shaped into ellipsis using optics with different focal lengths in *x* and *y* so that the orientation of the observed ellipsis is proportional to depth. Speckles of different sizes are used to obtain different depth accuracy depending on size. Figure 65.15a

shows the speckles pattern projected by the sensor and an image taken in the dark by photographer Audrey Penven showing the **IR** speckles. Figure 65.15b shows the components of the Kinect sensor and the corresponding RGB and depth images of a scene.

Time of Flight (TOF) Distance Sensors

Time of flight (**TOF**) sensors consist of a light source (usually a laser) that emits a continuous waveform and a special imaging sensor that measures the phase shift of the received signal in each pixel. The depth at each pixel is proportional to the phase shift. **TOF** sensors have been in the market for quite some time, but the need for allocating a large portion of the sensor to the decoding electronics has made it challenging to produce low-cost sensors at reasonable resolution. Some of the companies offering **TOF** sensor have been Mesa Imaging AG that produces the SwissRanger [65.10] sensors, Softkinetics [65.11], PMDvision.

Stereo Vision

Stereo vision is a well-known computer vision solution to the extraction of three-dimensional (**3-D**) depth maps in areas with sufficient texture to find image correspondences. As opposed to structured light or **TOF** sensors, stereo vision systems are totally passive, but require a calibrated stereo rig, and their performance depends on the level of external illumination and on the amount of texture present in images.

The selection of the optimal dense mapping sensor depends on the application. The laser distance sensor provides reasonable information for laser-based **SLAM** and obstacle detection and avoidance; however, it only provides range information on a plane as opposed to the dense **3-D** range offered by the structured light, **TOF**, or stereo systems. The structured light sensor uses a simple imaging sensor but requires additional computation to estimate depth in each pixel while the **TOF** sensor computes depth in each pixel at the expense of a sensor with lower fill factor. The stereo system does not require additional lighting, but requires an additional camera and a computation module to extract depth. Other parameters to consider are the maximum and minimum range that the sensor provides to ensure that it fits the requirements of the application in terms of mapping and obstacle detection.

65.2.2 Localization and Mapping

A robot that knows its location and understands its surroundings is able to plan intelligent maneuvers to achieve its goals. Localization and mapping are basic primitives that enable smart and efficient behavior. Early successful robots like the Roomba chose to sac-

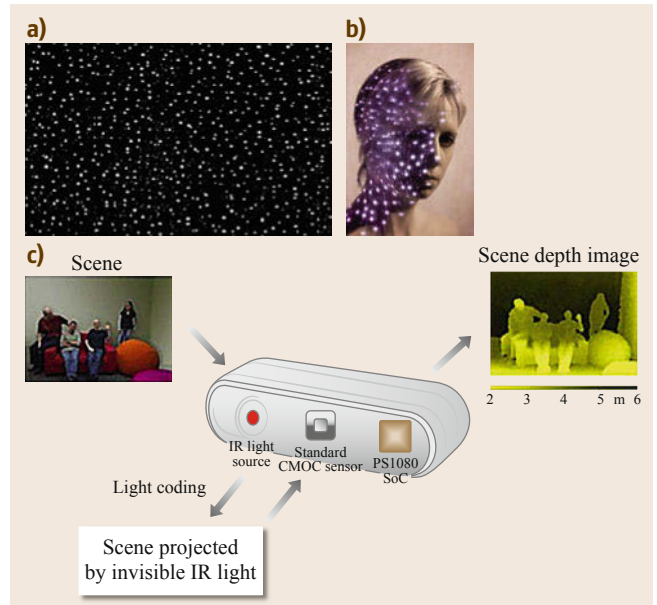


Fig.65.15a–c Primesense sensor: (a,b) Speckles pattern projected by the laser emitter. (c) Block diagram of the Kinect sensor

rific localization and mapping in order to achieve an appealing retail price since the localization and mapping technology was either too expensive or not existent at the time (many of the dense sensors presented in the previous section were developed after the Roomba). In recent years, a number of low-cost, yet powerful simultaneous localization and mapping (**SLAM**) technologies have been developed and integrated in floor-care products. These technologies are described in the following sections.

Vector Field SLAM

The Mint robot by Evolution Robotics uses active beacons for localization. The Northstar beacon projects two **IR** spots onto the ceiling that are modulated to simplify the detection of the spots with the sensor. The spots are invisible to the human eye and thus do not produce visual clutter. While placing the beacon can still be regarded as a modification to the environment, surveys among our customers suggest that the vast majority largely accepts setting up the beacon prior to running the robot [65.12]. The Northstar sensor uses 3 photodiodes to compute the direction to the spots from the measured current through the photodiodes. The photodiodes can be sampled at high frequency to detect the modulated spot frequencies for data association. The sensor is quite inexpensive and suitable for cost-sensitive applications. However, the sensor suffers from multipath since light not only reaches the sensor directly but also through reflections from walls

and other furniture, making the position computed by the sensor inadequate to be directly used for localization and mapping. The sensor is augmented with a localization method that learns the light distribution in the room through a simultaneous localization and mapping (SLAM) approach [65.13]. Figure 65.16 shows the Mint robot cleaning the environment depicting the operation of the Northstar localization system and the problem of multipath. The figure also shows the Mint robot and the Northstar cube and the Northstar sensor.

In vector field SLAM the spatial variation of continuous signals is learned and simultaneously used for localizing the robot by fusing information from dead-reckoning (odometry and gyro) and Northstar. In the following, this method is introduced and tailored toward measurements obtained from Northstar. The signal field is represented as a regular grid of fixed node positions $b_i = (b_{i,x}, b_{i,y})^T$, $i = 1 \dots N$, where each node $m_i \in R^4$ holds the expected Northstar positions of both spots when placing the robot at b_i and pointing it in a fixed orientation $\theta_0 = 0$. Vector field and robot pose are then estimated through the application of SLAM.

Let the robot path be a time series of poses $x_0 \dots x_T$, $x_t \in SE(2)$, i.e., the set of rigid transformations in the horizontal plane, and let $x_0 = (0, 0, 0)^T$. At each time step $t = 1 \dots T$ the robot receives a motion input u_t

with covariance R_t and a measurement $z_t = (z_{x1}, z_{y1}, z_{x2}, z_{y2})^T$ of the two Northstar spot positions with covariance Q_t . The spot positions are also each affected by the rotational variability denoted $c = (c_x, c_y)^T$. The rotational variability models errors in measuring the direction to the spots caused by not having the sensor perfectly level.

The SLAM problem is solved with the ESEIF-SLAM that is constant time and requires memory linear in the size of the area explored by the robot. The method has been implemented in the processor of Mint, an ARM 7 processor with 64 kByte RAM [65.13]. Vector field SLAM has been extended to address covering larger areas by using more Northstar beacons [65.15] and to provide a solution for the re-localization of the robot after it has been kidnapped or paused and resumed [65.16].

Figure 65.18 presents the map obtained by the robot after a cleaning run in a home environment of 125 m² covered by three Northstar beacons marked with the pink and green disks (units are in meters). The robot navigated in the home by following a cleaning strategy based on systematically covering sectors of the environment. As long as at least one beacon is visible to the robot, the strategy moves the robot onto a neighboring region until no space is left to clean. At the end the robot follows along the perimeter of detected obsta-

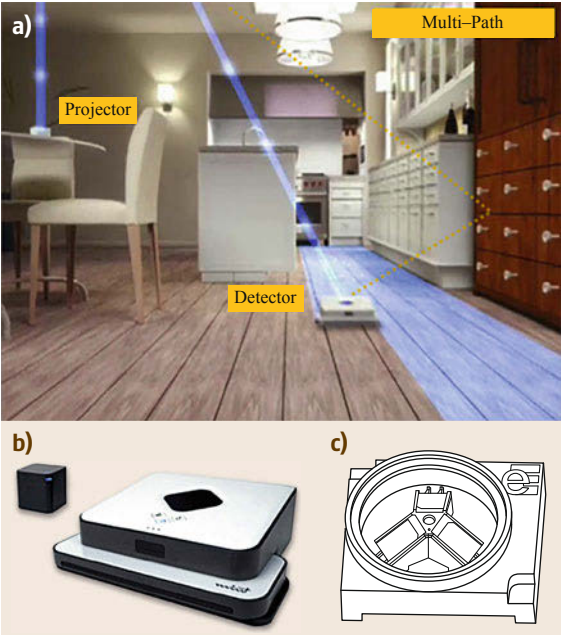


Fig.65.16a–c Mint robot. (a) Normal operation of the Mint robot using Northstar (the yellow path indicates multipath). (b) Mint robot and Northstar cube. (c) Northstar sensor

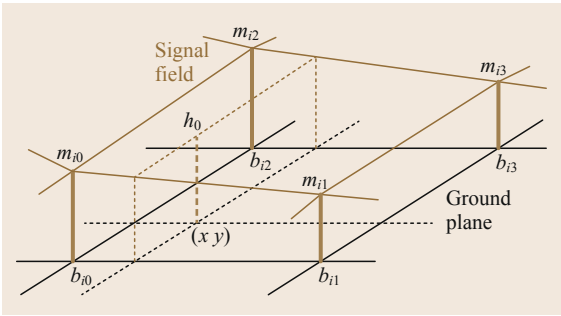


Fig. 65.17 Vector field SLAM with Northstar



Fig. 65.18 Robot map obtained with vector field SLAM in a 125 m² home environment

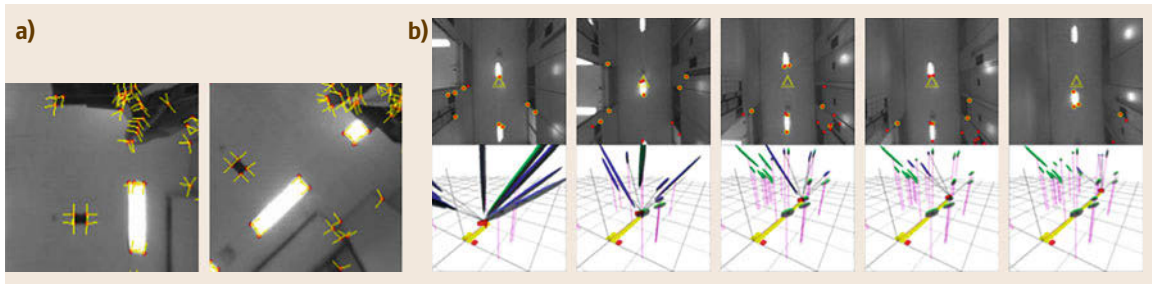


Fig. 65.19 (a) *cv-SLAM* (after [65.14]). (b) Features extracted by the vision front-end. Map obtained with the *EKF*

cles for a thorough cleaning around walls and furniture. As the robot moves through the environment it creates an occupancy grid map using the position information from localization. Each visited cell is classified into one of the following categories: obstacles (drawn in black), floor changes (drawn in brown), hazards (drawn in red), and free space (drawn in shades of blue that indicate visibility of the spots, the lighter the blue, the better the visibility).

Visual SLAM

Visual localization and mapping is attractive for a variety of applications due to the rich input and the low cost and footprint of visual sensors. The difficulties lie in robustly extracting a critical subset of information from the high-rate visual data stream and processing it efficiently to yield useful output. Despite steady increases in the computational power of most platforms, such challenges are nonetheless exacerbated by the limited processing and storage provided by low-cost, embedded systems appropriate for low-power applications or consumer products. Many state-of-the-art approaches to visual *SLAM* depend on a per-frame processing rate sufficiently high, relative to the speed of camera motion, to permit strong temporal assumptions on the image sequence. This section reviews two approaches to visual *SLAM* focused on domestic robots. Ceiling vision similar to the work of Jeong and Lee [65.14] can be found in the Navibot from Samsung, the Roboking from LG, and the Iclebo/Homerun from Yujin Robotics/Philips. Furthermore, visual *SLAM* systems have been developed for low-cost and embedded systems [65.17, 18].

cv-SLAM

The ceiling vision *SLAM* [65.14] system is composed of a camera facing upward, looking toward the ceiling. The system extracts corner features using a Harris detector and matches features using correlation. Feature matching achieves invariance to view point changes by training a set of multiview descriptors of the features as matching proceeds during the run. The main orientation(s) of the feature are further used as descriptors

of the feature to ensure a two-dimensional (2-D) rotation invariant feature matching that can be used for relocalization. The localization and mapping backend of the system is based on an extended Kalman filter (*EKF*) that fuses visual and dead-reckoning information (odometry and gyro) and that tracks the pose of the robot in a two-and-a-half-dimensional (2.5-D) (x, y, θ) and the 3-D position of the features (landmarks of the map). The orientation(s) of the features are also represented in 3-D and tracked with the *EKF* to predict changes in the feature patch due to motion of the robot (as the robot moves, features on the ceiling will undergo a rotation while features on the walls will experience a shearing transformation in addition to rotation).

Figure 65.19a shows corner points and their estimated orientations in views with rotation only. Figure 65.19b presents snapshots from a sequential map-building experiment on a corridor.

vSLAM

The *vSLAM* [65.17, 18] system from Evolution Robotics is designed for a low-cost robotic platform equipped with simple odometry and a single camera. Figure 65.20 shows the block diagram of the system. Operating primarily as a view recognition engine, the visual measurement front-end requires only occasional, weak assumptions on processing rate, and intrinsically provides robust loop closing when previously mapped areas are revisited. The visual measurements and odometry are fused in the back-end in a graph representation and optimized incrementally. The *SLAM* graph complexity is bounded during operation using variable elimination and constraint pruning, with heuristic schedules in order to keep optimization and storage costs commensurate with explored area, rather than with time of exploration, all while causing minimal loss in mapping and localization accuracy. The system has been evaluated on real datasets with planar ground-truth reference, showing that the system operates successfully even at frame rates below 2 Hz, running on an ARM9 processor with 64 MB of *RAM* [65.18].

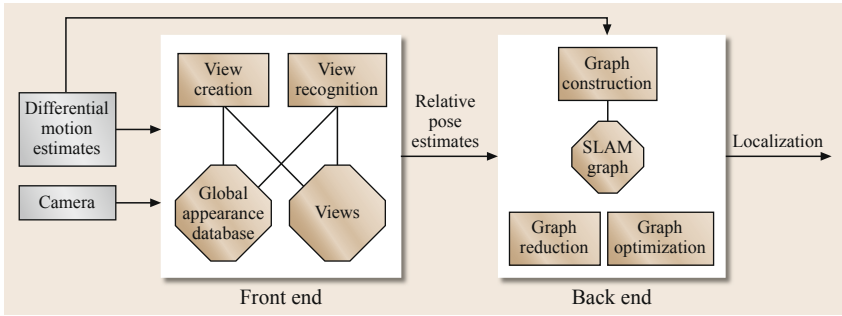


Fig. 65.20 vSLAM block diagram

View recognition engines [65.17–22] have proven attractive components for SLAM systems because they permit robust and flexible loop closing. Instead of making correspondences between individual features or measurements as in the *cv-SLAM* system, view recognition engines typically match constellations of features or entire images, without requiring tracking. vSLAM [65.17] creates views by first matching SIFT [65.23] features on pairs of incoming images, and second computing structure and motions estimates using bundle adjustment. The SIFT features are stored in a local database for each view and on a global database for the complete map. View recognition is performed by a feature lookup in the global database that provides a set of candidate view matches. Feature lookup in the local view database followed by robust outlier rejection and a local bundle adjustment completes the view recognition and visual pose estimation process.

Commonly used graph SLAM methods for agglomerating sensor information often incur computation and storage costs that grow with time, rather than with space explored. For a robot operating for extended periods within a limited spatial area – typical of practical applications – this is an undesirable trade-off. vSLAM [65.18] instead applies probabilistically sound graph reduction methods that limit the complexity of the graph to a linear factor of the complexity of the explored space. Past poses of the robot that are not used for view recognition can be marginalized out of the estimation, and their incident constraints are collapsed back into the graph.

Figure 65.21 presents the results of running the vSLAM system in two sequences, one collected in a regular household (*right*) (same house as the one shown in Fig. 65.18 for vector field SLAM) and the other collected in a large warehouse environment (*left*). The first set of plots show the ground truth path of

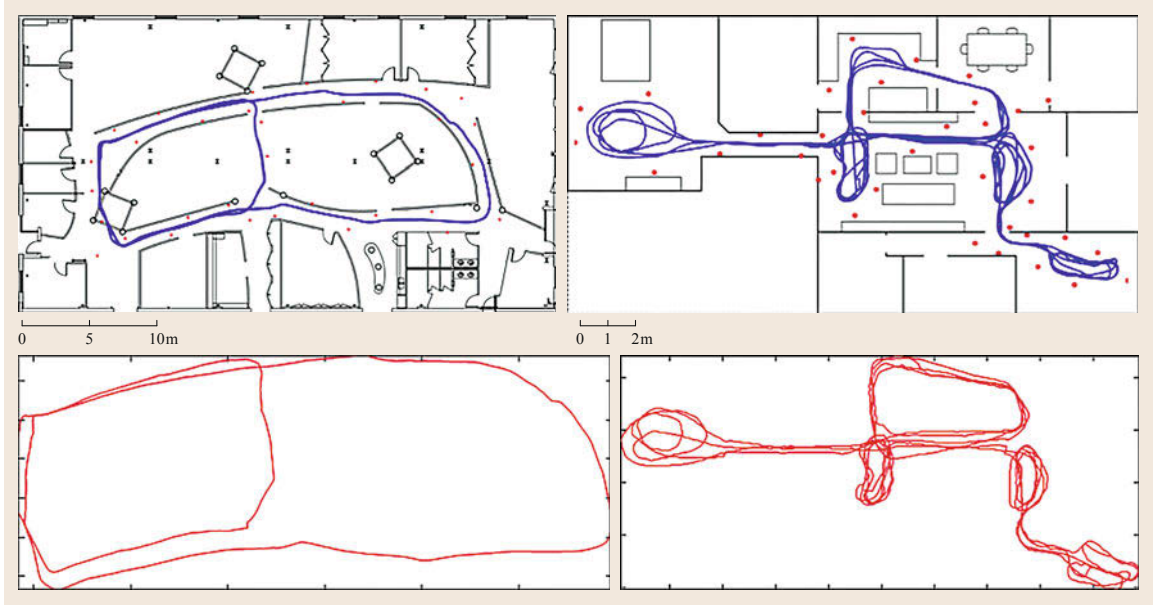


Fig. 65.21 vSLAM results on a warehouse environment and in a household environment

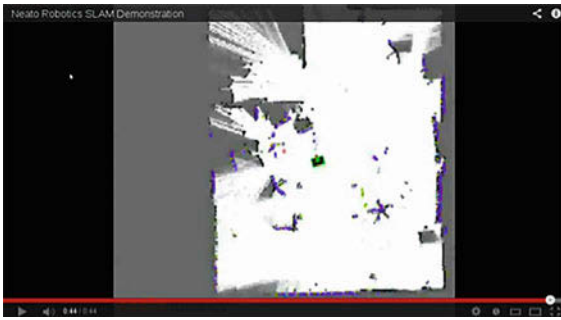


Fig. 65.22 Map created with the Neato XV-11 robot (www.youtube.com/watch?v=zodC8EFvh7g)

the robot and the floor plan of the environments. The second set of plots shows the trajectory of the robot estimated with vSLAM. The warehouse environment extends over an area of 24×12 m and the house over an area of 20×9 m. The estimated trajectory has a root mean square (RMS) error of 44 cm in the warehouse case and of 28 cm in the household case.

Laser-Based SLAM

The previous sections presented a number of low-cost solutions to the SLAM problem in which the data association was (almost) perfect. In the case of Vector-Field SLAM, the modulation of the spots of the Northstar cube ensures a unique identification of the spot. In the case of visual SLAM, the visual front-end incorporates a number of checks to ensure that misrecognitions are very rare. Laser-based SLAM has the characteristic that the measurements acquired with the laser are not unique since it is possible to obtain similar measurements in a variety of places in a household (just aiming the laser to a wall will provide measurements that are indistinguishable from a measurement to a different wall). In addition to the data association problem, laser distance measurement sensors, such as the one presented in Sect. 65.2.1, provide both range and bearing to the landmarks. Both Northstar and cameras give only bearing measurements to the spots or features.

The laser-based SLAM literature is quite extensive [65.25]. The estimation back-end could be an

extended Kalman filter (EKF), a Particle Filter, or a GraphSLAM system. Several data association algorithms are available, some of them are proactive (or even greedy) [65.26, 27] and some are lazy [65.28] in assigning correspondences between measurements and landmarks. The selection of the algorithm to implement in the domestic robot would be guided by the trade-off between computational resources and the performance requirements. Figure 65.22 presents a map obtained with the Neato XV-11 robot.

65.2.3 Navigation and Coverage

The Trilobite robot vacuum cleaner by Electrolux was one of the pioneer robots to be commercialized. The trilobite was equipped with a sophisticated custom sonar sensor system that allowed the robot to navigate without touching obstacles (or touching them very gently). The coverage strategy consisted of two stages: first, explore the perimeter of the room to estimate the area to clean and second, cover the room with wall-to-wall diagonal passes. The perimeter exploration stage assumes that the robot would eventually traverse through the complete boundary of the area to clean and return to the charging station (Fig. 65.23a).

As mentioned previously, the cost constraints forced early robots like the Roomba to eschew advanced features like localization and mapping in order to offer a product at a price point accepted by consumers. Nevertheless, the navigation strategy implemented in the Roomba was quite effective in covering the space, especially when running in single rooms or in presence of large amount of clutter. The Roomba uses a spiral pattern in open area to optimally cover the space without localization until it hits an obstacle (Fig. 65.23b). Then it selects random orientation and continues moving in straight line until reaching the next obstacle where it selects another random orientation to continue with the same behavior. The spiral can be triggered when the robot travels for a certain distance without having found any obstacles. Many of the other random robots present in the market have a strategy that follows similar principles to the Roomba one.

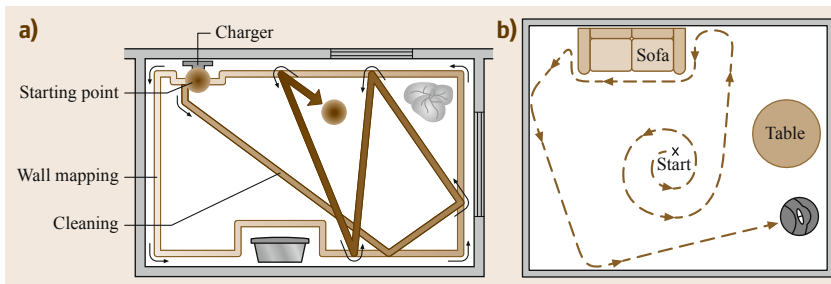


Fig. 65.23a,b Coverage strategies. Trilobite strategy. Roomba strategy [65.24]

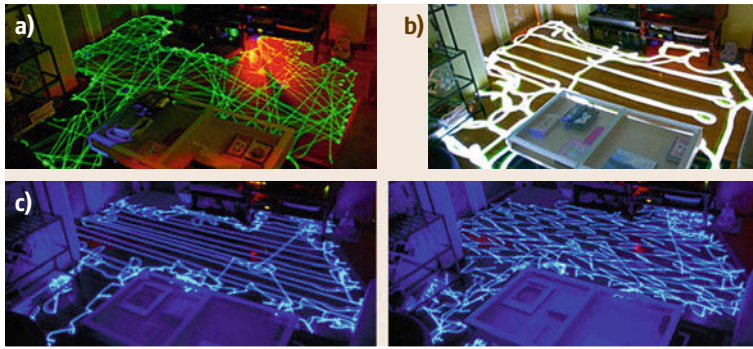


Fig.65.24a–c Long exposure images [65.29] showing the coverage strategies of the (a) Roomba, (b) Neato, and (c) Mint

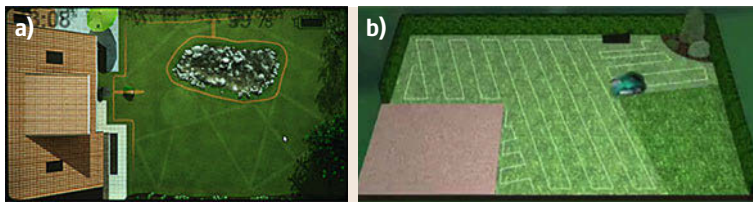


Fig.65.25a,b Coverage strategies for lawnmowers. (a) Tango [65.30] by John Deere and (b) Indego [65.31] by Bosch

The systematic robots on the other hand take advantage of the localization system to plan efficient cleaning paths to maximize coverage in the least amount of time, pause for charging on the docking station and resume cleaning from the last cleaned spot, and intelligently navigate from room to room. Mint takes the strategy of focusing first on open area cleaning, covering the space in parallel straight passes to traverse as much open space as fast as possible, and then performing a final cleaning on the perimeter and around the obstacles. This perimeter cleaning step enables Mint to uncover portals to new areas that were not encountered during open area cleaning. Other robots like the Navibot from Samsung, the Roboking from LG and the iClebo from Yujin/Philips use a similar strategy without the final perimeter cleaning. The Neato XV-11, on the other hand, performs first an exploration and cleaning of the perimeter of the environment in order to create a good localization map and then completes the coverage of the open area. Figure 65.24 shows long exposure pictures of different robots: Roomba, Neato, Mint sweeping and

Mint mopping. These long exposure pictures show the trajectory of the robots during normal cleaning operation.

The lawnmower robots use similar coverage strategies to the ones of vacuum cleaner robots. One element common to all lawnmower robots is the usage of an embedded wire to define the perimeter of the lawn. Within the boundaries defined by the wire, some robots like the Automower from Husqvarna or the Robomow from Friendly Robotics use a complete random coverage strategy. The Tango from John Deere combines straight motions in random directions with spiral motions (a-la-Roomba). The Indego from Bosch is the only robot that attempts to systematically cover the space by first exploring the perimeter to estimate the size of the lawn and then traversing the interior with parallel straight passes. Systematic coverage is enabled by fusing sensory information from wheel odometry and an inertial measurement unit (IMU) by means of probabilistic reasoning with prior knowledge. Figure 65.25 depicts the coverage strategies of the Tango and the Indego.

65.3 Smart Homes

Several attempts have been made in the literature to define the term smart home, for example, in [65.32] the term is defined as *the latest expression of the various ways in which technology in the home has developed*. In [65.33], the notion of a smart home is defined more explicitly as:

a residence equipped with computing and information technology which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security and entertainment through management of technology within the home and connections to the world beyond.

Smart homes typically comprise elements such as network of sensors and actuators, and also entire robotic systems.

In 1999, a company called e2 Home was established by Ericsson and Electrolux to explore the possibilities of smart homes [65.34]. E2 Home built several houses with smart home devices using IT technologies. Through the exploration, several issues relating to smart homes from business point of view have been unveiled, which include the difficulties relating to the complexity of the system, starting up the new business model, handling of intellectual property rights (IPR) for the third parties contents, and the consumer's needs. The company was liquidated in 2004.

Current smart home technology includes video monitoring, motion detectors, fall detectors, pressure mats, environment control, health monitoring such as blood pressure, pulse rate, body temperature, weight, and human computer interaction (HCI) technology, for example, to recognize gestures. Smart homes also often refer to houses connected to a smart grid, which is defined as [65.35]:

a developing network of new technologies, equipment, and controls working together to respond immediately to our 21st century demand for electricity.

In this case, the smart home is defined as [65.35]:

a residence with the capability of efficiently controlling generated solar energy and power consumption making it ideal for vehicle power supply and management.

The development of smart homes requires a number of technical questions and challenges to be addressed [65.32]: how to convert current home structures and architectures into smart homes, how to standardize smart home components, for example, sensor networks, how to keep the equipment cost at a reasonable level, and how to deal with security and privacy issues.

In the following sections we will describe a number of prominent smart home developments, the Aware Home at Georgia Institute of Technology, the Gator Tech Smart House at the University of Florida, and the sensorized environment for life (SELF) at AIST (the Japan National Institute of Advanced Industrial Science and Technology) (Figs. 65.26, 65.27). These developments show that current smart home technology goes significantly beyond existing home automation. Accounting for the significant increase in the elderly population in the near future, many of today's smart home developments pay special attention to improving the quality of life of elderly people. The

descriptions below will also address the question on how to integrate robotics systems into smart home concepts.

65.3.1 Gator Tech Smart House

The Gator Tech Smart House (Fig. 65.26) was built at the University of Florida [65.36]. It addresses the needs of elderly people to live independently and maintain dignity and quality of life at older ages. The house is equipped with many smart devices such as smart floors, tracking the motion of the occupants of the house, smart blinds, automatically adjusting ambient light, smart display, smart cameras, smart phones that can act as a remote control to other appliances, location tracking, smart leak detectors, and smart beds. The exterior of the house has a smart mailbox which alerts residence if mail is delivered and a smart front door which can sense home owners using an radio frequency identification (RFID) tag, allowing keyless entry to home owners.

The kitchen of the Gator Tech Smart House includes a smart microwave, which uses RFID on food packages. This allows the microwave to adjust the settings for cooking the meal. It also informs the resident about the readiness of the meal. The kitchen further comprises a smart refrigerator that monitors food availability and consumption, and detects expired food items. The smart refrigerator can create shopping lists automatically and has an integrated meal preparation advisor based on items in the refrigerator and pantry.

The implementation of such a complex system has raised a number of technical issues and questions, including the development of the smart devices, data handling of networks of sensors, and interconnecting smart devices to other devices in the environment. These questions led to some new research tracks on smart houses, primarily grouped into pervasive computing and mobile computing network research.



Fig. 65.26 Georgia Institute of Technology: Aware Home

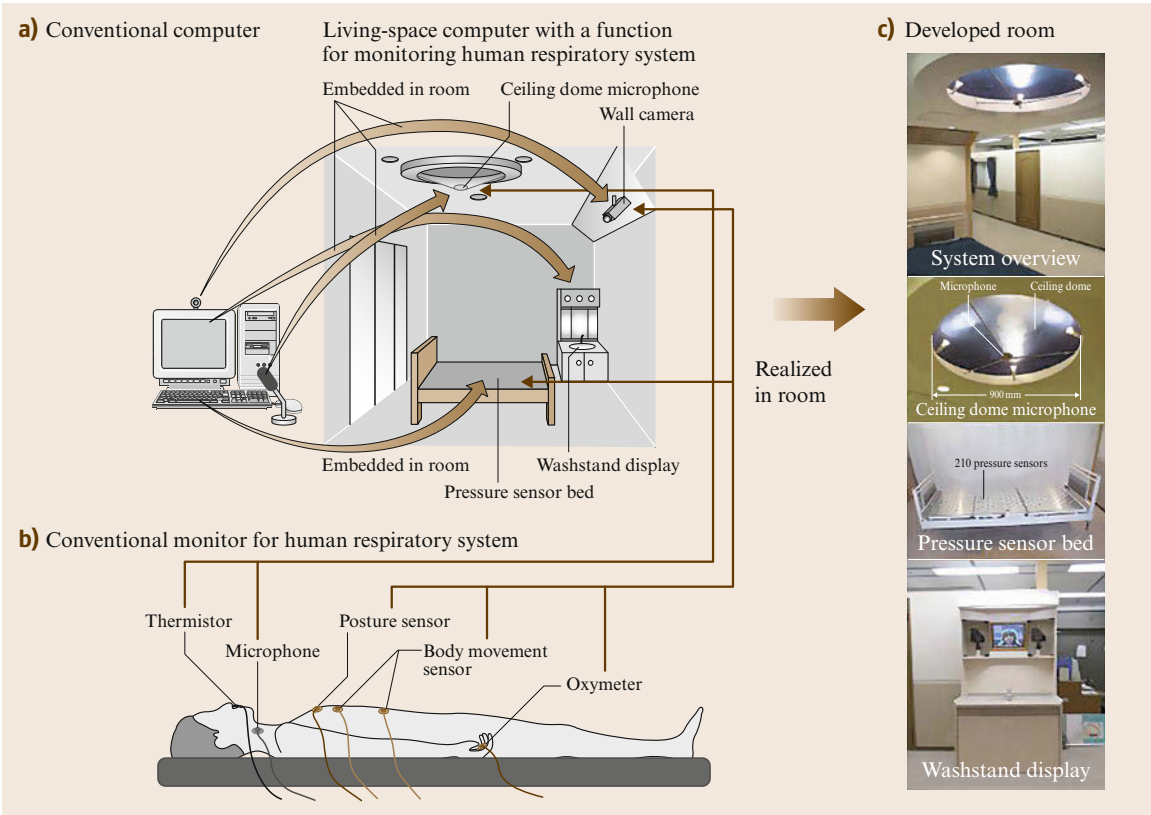


Fig. 65.27 AIST, the sensorized environment for life

65.3.2 Aware Home

Aware Home is a living laboratory for research in ubiquitous computing for everyday activities. This project is conducted at Georgia Institute of Technology [65.37]. The major objective of the Aware Home project is to build an environment that is capable of being aware and keeping track of the states and activities of its inhabitants. Aware Home creates a partnership between the resident and the surrounding sensing and computing technologies. This opens several fields of research, not only from the technology point of view, but also in terms of the social aspects of the inhabitants. The main research agenda of Aware Home spans human-centered and technology-centered research, software engineering, and social implications.

Technology and application-centered research focuses on sensor networks, distributed computing, context awareness and ubiquitous sensing, individual interaction with the home, smart floors, and finding lost objects. Research on context awareness is inspired by the fact that humans communicate with each other very success-fully by referring to what is called shared

context. For communication between humans and computer systems, this shared context must be made explicitly. Sensor systems, which facilitate the extraction of context, need to be developed.

This human-centered research focuses on support for the elderly and other social issues. A key concept in sup-orting the elderly is *aging in place*. Aware Home is designed to support the elderly and allow them to be independent instead of moving to elderly care facilities. Supporting the elderly leads to the study on cognitive support such as reminding them when to take medication, guiding them when they lose their way, and locating lost items.

65.3.3 SELF – Sensorized Environment for LiFe

SELF stands for Sensorized Environment for LiFe [65.1]. The objectives of SELF are to develop a network of sensors which are embedded in the environment, information gathering using the networked sensors, storing and analyzing the information, and the reporting of useful information to assist and maintain good health. The basic advantages

of **SELF**, due to the embedded nature of the sensors are:

1. No limit on size, weight, or power source,
2. It does not disturb the human,
3. It does not impose physical restrictions, and
4. Sensors are rarely broken since they are fixed to the environment.

SELF can be viewed as a system that monitors a person's behavior or activity and represents the data objectively in an approach known as self-externalization. **SELF** is motivated by the fact that humans sometimes cannot notice a change in their condition which affects their health without a medical doctor. Therefore, the use of network sensors to monitor human behavior and re-

port useful information that greatly affects the health status will further improve quality of life.

The **SELF** study considers behavior as a means of communication, and sensors embedded into the environment as one way to observe a person's behavior. The **SELF** implementation consists of a bed with a sensor, a ceiling with microphones, a washstand with a display, etc. The bed with sensors can determine the time the subject sleeps and wakes up, their posture during sleeping, and their breathing pattern. The microphones attached to the ceiling can detect snoring or normal breathing sounds. Based on the monitored data, the washstand display is used as an output device to provide the subject's health status and thus create feedback to the subject.

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-  **VIDEO 731** Husqvarna Automower versus competitors
available from <http://handbookofrobotics.org/view-chapter/65/videodetails/731>
-  **VIDEO 734** Windoro window cleaning robot review
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-  **VIDEO 744** Test-Driving Beam, the telepresence robot
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-  **VIDEO 745** Beam's new Palo Alto store lets telepresence robots sell themselves. Literally
available from <http://handbookofrobotics.org/view-chapter/65/videodetails/745>
-  **VIDEO 746** This robot is your running coach – Joggebot
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-  **VIDEO 747** RUFUS – your personal running coach
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66. Robotics Competitions and Challenges

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This chapter explores the use of competitions to accelerate robotics research and promote science, technology, engineering, and mathematics (STEM) education. We argue that the field of robotics is particularly well suited to innovation through competitions. Two broad categories of robot competition are used to frame the discussion: human-inspired competitions and task-based challenges. Human-inspired robot competitions, of which the majority are sports contests, quickly move through platform development to focus on problem solving and test through game play. Task-based challenges attempt to attract participants by presenting a high aim for a robotic system. The contest can then be tuned, as required, to maintain motivation and ensure that the progress is made. Three case studies of robot competitions are presented, namely robot soccer, the UAV challenge, and the DARPA (Defense Advanced Research Projects Agency) grand challenges. The case studies serve to explore from the point of view of organizers and participants, the benefits and limitations of competitions, and what makes a good robot competition.

This chapter ends with some concluding remarks on the natural convergence of human-inspired competitions and task-based challenges

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in the promotion of STEM education, research, and vocations.

The idea of promoting science and technology through competitions became pervasive at the end of the 20th century [66.1]. Since then, competitions have been promoted in several fields, taking a broad range of formats,

goals, and target audiences. The main aims underlying this trend are to create a motivating framework for science and technology, and to support the development of skills, ideas, and technical solutions.

66.1 Introduction

These objectives fit particularly well with the field of robotics, since the design and implementation of robots is a great challenge for a competition. Robots are physical artifacts, whose design and implementation require creativity, technical skills, and scientific knowledge. Arguably, Robotics is nowadays the field where competitions have the strongest impact.

The competitions that aim at the design and implementation of robots cover the whole spectrum of the educational chain, from young pupils of the elementary schools to senior researchers, such as the authors of this chapter. Moreover, there is a large world of hobby robot competitions, that we will not specifically address in this chapter. The focus of this chapter are those initiatives that are specifically targeting autonomous robotics research and education.

Another ingredient that makes robotic competitions very successful is that robotics requires a great deal of integration. Consequently, building a winning team requires a substantial cooperation among team members with very different skills and backgrounds. This creates an ideal playground to address teamwork within educational programs, and an engineering challenge for higher level students and researchers. The level of per-

formance that robots achieve in the competitions is often compelling, as compared with the prototypes that are developed within conventional research projects. In this respect, competitions provide an outstanding testbed for scientific and technical solutions.

Robotic competitions can have great appeal for a general audience; thus, robotic competitions are also a very effective tool to bridge the gap between citizens and the progress of science and technology.

There are several features that can be used for the classification and presentation of competitions. We have chosen to distinguish between competitions where the contest mirrors a traditional human contest and competitions where robots are challenged to perform some task. The task whose achievement, once mature, would extend the possible uses of robots in our society.

Next we present an overview including past robot competitions and considerations that apply across all robot contests. We then focus on human-inspired contests with a case study on robot soccer. Later we review task-orientated contests with case studies on the UAV challenge and the [DARPA](#) grand challenges. The chapter ends with concluding remarks on lessons learned thus far in robot competitions.

66.2 Overview

The history of robot competition begins with the Micromouse contests. In 1977, the IEEE Spectrum magazine announced their intention to hold an *Amazing Micromouse Competition*. The contest took the form of a time trial where a small wheeled robot *mouse* raced to complete a maze in the shortest possible time. The first event to be held was in New York in 1979 and saw over 6000 entries. However, the field rapidly shrank to 15 competing *mice*. This first contest of these early autonomous robots was won by a simple wall-following robot. While a valid victory, the rules for future events were swiftly changed to move the goal point from the edge of the maze to the center, ensuring that the path search aspect of the problem was emphasized [66.2]. The micromouse contest then became very popular across Europe, then later Japan and then back to the USA by the mid-1980s. Micromouse events continue to be held to this day, including contests from India and South Korea. The contest which began as a struggle to develop a device that could reliably traverse corridors without jamming, is now a highly optimized contest where precision machines complete the maze in under 5 s [66.3].

Seeing the success of the micromouse competition and the power to inspire science and technology ed-

ucation, Dean Kamen conceived the For Inspiration and Recognition of Science and Technology or *FIRST* robot competition. In the *FIRST* robot competitions high school teams would compete to build and program a robot to complete a challenge. The original challenge in 1992, titled *Maize Craze*, involved herding balls into a home goal. Since then the challenge, from stacking containers to throwing flying discs, has been changed year to year while keeping the basic structure of the contest the same. The contest, like the Micromouse contests, have expanded internationally and continue to this day. In 2014, the competition is projected to involve 68 000 students [66.4].

Meanwhile, in the early 1990s, the advances and limitations of game playing computers, and the need to evaluate competing algorithms in mobile robotics converged toward the concept of a new competition for academic robotics: robot soccer [66.5–7]. We will continue this discussion in Sect. 66.3.

In 1995, restlessness at the pace of innovative change since the space race of the 1960s sparked aerospace entrepreneur Peter Diamandis to propose the X-Prize. Ansari X-Prize was a \$10 million prize to demonstrate a functional privately developed space pas-

senger plane [66.8]. Rekindling the idea of racing to achieve an ambitious task was captivating and caused ripples through the scientific community [66.1]. The inspiration spread to other fields and funding bodies resulting in many initiatives such as the UAV challenge and the [DARPA](#) grand challenge which we discuss in Sect. 66.4.

Robotics is well suited to innovation through competition. As this handbook testifies the field of robotics is broad and covers research in mechanical design, electronics, control theory, signal processing, software engineering, and machine learning to name a few. In addition to the breadth of the field the nature of the research also requires one or more agents interacting with the physical environment, thereby limiting the use of techniques common to other technical fields to share and validate their research.

Standard techniques such as: standardized tests (which are commonplace in science and engineering), shared test data sets (such as those used in image processing and machine learning communities), and reference implementations (used in computer science algorithm evaluation) are invaluable in robotics but cannot cover the full scope of a robot system operating in the world. Indeed, many components used in robotic systems can be tested in isolation with these same techniques; however, as the components of a robot are integrated into a system of systems interacting with the physical world the limits of the above methods becomes evident. In terms of test methodology: unit and integration level testing are well served; however, system, dynamic and, in particular, acceptance testing of innovation across the field was missing. An answer came in a resurgence back to the roots of robotics and in favor of robot competitions.

The range of robot scientific competitions is very broad, and in this section we look at them from different perspectives, aiming at providing an overview of the settings that have been developed so far. To this end, in the following we address a number of aspects that are relevant to the design and implementation of a robot competition.

66.2.1 Aims and Targeted Participants

As suggested in the introduction, the competitions that are addressed in this chapter are those focussed on research and education. These two aspects are often deeply inter-related. On one hand, there is always an educational component in any research involving a team with different backgrounds and different levels of expertise. Moreover, if one looks at competitions as an educational tool, they represent one of the most advanced forms of education; consequently, they specifically at-

tract teachers and mentors that are involved in research on education. Although research and education are related to one another, the balance between research and education is naturally significantly different across the numerous robot competitions.

66.2.2 Competition Challenges

Each competition relies on a challenge and there are several ways of categorizing them. While competitions are nowadays mostly among robots and not robot-vs-human, a large group of competitions take inspiration from human competitions, ranging from soccer, to the Olympic Games. These competitions have an explicit or implicit underlying assumption of comparing robot performance with human performance. The other kind of challenge aims at a proposing a specific problem to be addressed using machines the hope is that by racing to achieve the aim, new capabilities can be matured faster into future robots.

66.2.3 Types of Robots

Another key element for classification of competitions is the robot type. Any kind of robot is conceivable for use in competition. Robot choice is driven by the competition format and targeted participants. The use of commercially available robots and robot kits enables less mechanically focused participants to move forward quickly. The use of homogeneous sets of robots enables competitions to be fought on algorithmic innovations over robot manufacturing skill. An unrestricted category of robot type can be useful for some task-based challenges, where a novel physical design may be the key in simplifying the problem and achieving the objective (such as in rescue robotics).

66.2.4 Competition Scenarios

The scenario is largely determined by the challenge addressed, be it a competition among soccer robots or among service robots operating in a home environment; consequently, there is a broad variety. In some cases, the scenario is fixed and known before the competition, such as in robot soccer; in other cases, only a general description is provided beforehand and the actual competition scenario is not known in advance as, for example, in search and rescue competitions. The competition scenario has deep implications not only on the setup of competition venues, but also on the participating teams. Practice environments for teams in lead up to competition must be representative, while not prohibitive to construct. From Lego robot soccer to the [DARPA](#) Robot challenge simple readily available hard-

ware store materials have been the material of choice for contest environments.

66.2.5 Safety

In some cases, the competition raises safety issues for the participants. This is the case for example of UAV competitions, and proper measures need to be taken in order to ensure a satisfactory level of safety. Moreover, the organizers must carefully address regulations for deployment of unmanned vehicles and/or use restricted access areas for the competition.

66.2.6 Qualification

Competitions with a large number of participants, such as education programs, can require regional and qualifying rounds similar to traditional sports leagues. When contests require a substantial effort and expense to participate funding agencies may make grants available to teams which succeed at a qualifying round to contribute to the cost to compete. Diverse selection criteria for satisfactory progress may well be considered in this case including justification of sound financial backing to complete the competition.

66.2.7 Evaluation

Evaluation is one of the key features of competitions both in terms of education (students must deliver a working solution) and in terms of research, where the integration of components is not a straightforward engineering practice. However, competitions also provide a great opportunity for developing benchmarks and new test methods: performance evaluation is an open issue in robotics and competitions are providing significant insights into the development of reliable and repeatable measures and testbeds.

66.2.8 Organization

Competitions are typically originated by a perceived need by a related scientific interest group, such as

a conference (e.g., AAAI, ICRA), a research funding agency (e.g., DARPA, ESA) or an entrepreneurial private company. Once established an ongoing competition founded by the first two groups will often be ran through a dedicated not-for-profit foundation. However, increasingly, education is a large business and competitions are becoming a significant activity therein; moreover, companies that help running competitions as projects are now on the market and production companies are now looking at competitions as viable tools for beyond state-of-the-art product development (not restricted to robotics) and for promoting their products.

66.2.9 Sponsors

The organization of a competition requires a substantial effort and budget. There are, however, several sources for acquiring the necessary resources. A first category of sponsors are schools that undertake competitions as part of their educational activity. The other natural sponsor are the funding agencies that institutionally provide support to research in robotics. The involvement of funding agencies can be many fold, ranging from the whole creation of a competition to the support of specific event, in particular at the local level. Another kind of sponsorship comes from public institutions that may regard competitions as a mean to drive citizens' attention on scientific and technological development. Robot manufacturers are also interested in sponsoring competitions that promote the use of their products. Besides promoting specific competitions, companies are also generally interested in supporting competitions as a form of advertisement. This is obviously related to the kind of visibility competitions can reach on the media. Moreover, companies may sponsor teams of young students as a form of recruitment and supporting education.

As the earlier discussion shows, a successful robotic competition not only requires to put forward a grand challenge or target specific societal needs, but it also requires a careful design and implementation.

66.3 Competitions Inspired by Human Competitions

In this section, we focus on competitions among robots that take inspiration from human competitions. The challenges that have been driving a lot of research in Artificial Intelligence, such as chess, go, checkers, are inspired by human competitions/games, but they do not address the interaction with physical world. On

the other hand, robotic competitions that are inspired by human competitions are typically connected with sports. A variety of sports have been addressed, from Olympic games [66.9, 10], to robot soccer [66.11, 12], to other competitions, such as sailing [66.13] or racing [66.14].

The distinguishing feature of this category of competitions is the grand challenge not only of emulating human performance, but to do this in the context of a human competition. Consequently, the robot is in principle humanoid, although several other platforms have been used, creating games for robots on wheels, given that, at this stage, it is a much simpler and accessible locomotion. It is worth noticing that a big push to this kind of competitions was given by companies such as Sony or Honda, which developed humanoid platforms also as showcases of their research and development activities.

One additional challenge that characterizes the human-inspired competitions is that several of them involve multiple robots. This feature has several significant consequences, not only in terms of the requirements on the teamwork among the robots, but also on the teamwork of the development team.

The scenario of these competitions is mostly outdoor; however, due to both technological and practical reasons often they take place indoor. On the one hand, platforms that are waterproof, work on grass or uneven terrain are unavailable or much more difficult to realize; on the other hand, practical considerations suggest to keep participation affordable and accessible.

One important feature of human-inspired competitions is that they aim also at providing some entertainment for the general public. Therefore, a suitable balance between technical difficulties and level of performance is needed. It is worth noticing how the general public is more keen to accepting the limitations of robots in playing soccer than in accomplishing a mission in Fukushima plant. Consequently, even games with slow and somewhat disappointing performance can generate participation, interest, and even strong emotions in the audience.

Human-inspired competitions span over the whole spectrum of participants, including both research oriented and more educational targets. In all cases, the type of competition creates an interest both in young generations that are naturally attracted by their ludic character, and in more mature researchers that aim toward the scientific challenges that they embody. A consequence of the intuitive appeal exerted by human-inspired competitions is that they easily attract large numbers of participants. Indeed, a frequent pattern of participation is to start with games and then move to other kinds of competitions that target socially or business relevant goals. In some cases, this endeavor is encouraged by the presence in the same event of both types of competitions.

The evaluation of the performance, in the case of human-inspired competitions, is very clear and amounts to winning the game. There are, however, examples of

specific capabilities associated with the game that are individually evaluated.

Given the reference provided by human competitions, human-inspired robot competitions typically have a permanent nature and a structure with local qualifying events. Consequently, there is an organization body managing the competition across the years and the main ones are nonprofit organizations (NPO)s. There are, however, commercial opportunities and companies that are interested in the deployment and sale of their robots. At present, these companies are mostly sponsoring the events, and often provide special offers for their products to the teams that enter the competition.

As mentioned earlier, human-inspired competitions have a strong appeal to the general public. Consequently, public organization often endorse and support them within their initiatives aiming at public awareness and promotion of science and technology. According to a common pattern, this may also attract large companies that invest some of their marketing budget in supporting socially and scientifically targeted events.

The ultimate consequence of the above sketched scenario is that the human-inspired competitions have a large impact on the general public. We have seen reports on human-inspired competitions in the media not only in the sections that typically cover science and technology, but also in the general news, and sometimes, even in connection with sport reports.

Besides this somewhat indirect effect, there are two major direct impacts of human-inspired competitions: on education and research. The renovation and advancement of the school system is embracing competitions for two major reasons: they motivate pupils and they teach key skills that are typically not addressed by conventional curricular activities. Human-inspired robotic competition perfectly fit both purposes. As for research, the scientific challenges, that have been put forward, whether or not they will turn out to be too ambitious, have gathered the attention of significant number of researchers, have driven a large body of research and have given rise to a number of side-effect developments: they are therefore fulfilling a role that is nowadays essential in the overall effort for advancing science and technology.

Robot soccer has a significant role within this category of competitions. The idea of robot soccer was discussed by several researchers in the early 1990s [66.5, 6]. Shortly afterward, Robot soccer competitions have been designed, in several venues, including Federation of International Robot-soccer Association (FIRA) [66.11, 15] and RoboCup [66.7, 12, 16].

In the next section, we address in more detail the RoboCup competitions. RoboCup remarkably started with the statement of a challenge, by *Hiroaki Kitano* and the initial RoboCup cofounders [66.7], namely

Table 66.1 Five subleagues of the RoboCup soccer games

League	Soccer players	Perception	Reasoning	Actuation	Communication
Simulation (Fig. 66.1)	(11) Software agents, 2-D (two-dimensional) and 3-D (three-dimensional) biped	Server engine	Client per team	Physical motion and perception	Explicit
Small-size (Fig. 66.2)	(5) Custom-built wheeled robots	Centralized overhead camera	Centralized offboard	Fast ball/robot speed, kicking, dribbling, passes, goal shots	Dedicated Radio
Middle-size (Fig. 66.2)	(5) Custom-built wheeled robots	Onboard, omnidirectional	Large-space control	Kicking, goal defense	Dedicated WiFi
Standard platform (SPL) (Fig. 66.3)	(5) Purchased legged robots	Onboard, directional range	Distributed	Legged, kicking, goal defense	Dedicated WiFi
Humanoid (Fig. 66.4)	(3,4,5) Custom-built, or purchased, biped multisized robots	Onboard, directional range	Distributed	Legged, kicking, goal defense	Dedicated WiFi

that *By the year 2050, there would be a robot soccer team that would be able to beat the human World Cup team*. With such long-term goal, RoboCup is an ongoing competition, that aims at research, educational, and engineering challenges through a set of testbeds that implement soccer games among robots. The competition keeps evolving every year, by yearly evaluating the performances of the robots and generating roadmaps toward its goal.

66.3.1 Case Study: Robot Soccer

The first organized RoboCup competitions took place in 1997 [66.16], and significant progress is noted every year. Interestingly, starting in 2007, and yearly thereafter, a team of five human players (volunteers from the RoboCup Board of Trustees) plays a demonstration game with the best robot team of the middle-size league, which we introduce below. Furthermore, each RoboCup competition event includes a symposium, which highlights research and development contributions relevant to the RoboCup competitions, and also to general robotics problems. As of 2014, the robots can play the basics of the game, with great speed and accuracy, but are clearly largely noncompetitive with human players. There is still a long way to go for RoboCup to reach its goal, but RoboCup continues to achieve annually increasing success, scope, and wide participation.

RoboCup soccer games are structured in five subleagues, where robots have different sizes and different capabilities, as overviewed (Table 66.1).

Many scientific challenges are addressed through different league settings, including teamwork and strategic decision making, in particular with systems of multiple robots in adversarial environments. To this end, the setup of each competition has evolved along the years from the initial proposal [66.7]. The simulation, small-size, and middle-size leagues were the

initial leagues in 1997. The standard platform league, started as a demonstration in 1998 and as a competition in 1999, was played with the Sony AIBO quadruped robots until 2007, and since 2008 with the Aldebaran NAO robots. Finally, the Humanoid Robot League started in 2000 with team-built biped robots that could barely stand on one leg to kick, probably to the most compelling derivative in improvement, leading into 2012 to biped robots of a variety of sizes that play complete games.

We now briefly describe the individual goals and set up of the soccer leagues, aiming at discussing the technical challenges and solutions devised. A summary of the complete technical contributions is found in the RoboCup symposia proceedings [66.16–32] (VIDEO 385).

Simulation

The RoboCup simulation league was developed from the very beginning of RoboCup, as an 11-player two-team simulation server environment, the SoccerServer, conceived and implemented by Noda [66.33]. The simulation league consists of a client-server architecture in which each of the two client teams is given, as an input by the SoccerServer, the state of the game (players state and ball position), and generates actions for the simulated robots, which are passed to the server for simulation of the new state of the world. Given the controlled realistic simulated environment, the goal of the league is to enable the researchers to abstract from the complications of real hardware and focus on teamwork architectures and coordination, strategic decision making, and learning in complete teams of 11 players. Initially, the league was a 2-D simulation, and since 2009, and following its roadmap to the RoboCup goal, it was extended to include a 3-D competition, leading to the current two subleagues: the 2-D and 3-D Simulation Leagues (Fig. 66.1).



Fig.66.1a,b Simulation leagues: (a) 2-D and (b) 3-D



Fig.66.2a,b RoboCup soccer leagues: (a) small-size robots and (b) middle-size robots

In the 2-D simulation subleague, the SoccerServer simplifies the environment by representing robots as basic circular elements, though with orientation and different capabilities in terms of perception and actuation. The client teams focus on effective team composition and on the strategic aspects of the game. In the 3-D Simulation subleague, the players are simulated biped humanoids. The teams need to address low-level control of such humanoid robots, including the creation of their basic behaviors, such as biped walking, running, kicking, turning, and standing up. In addition, the teams design and implement multi-agent higher level behaviors for realistic humanoid robot teams. The 3-D simulation league is currently tightly connected to the standard platform league, as the simulated humanoid robots are based on the characteristics of the Aldebaran NAO humanoid robots, as used in the RoboCup standard platform league (see in the following). The goal is to directly transfer techniques and approaches from simulation into real robots. Both the 2-D and 3-D servers are open software projects.

Small Size

The RoboCup small-size league (SSL) has been in place since the initial RoboCup in 1997. The league is set up as a field of predefined dimensions for teams of custom soccer robots of predefined small dimensions. Initially the teams were of three robots, and later have been increased to five robots. The initial playing field was a green ping-pong table, which was selected pragmatically by the founders in 1996, in order to make the specifications of the newly created RoboCup competi-

tion accessible to any research team in the world. A few years later, the field became green carpeted with white line markings, and its size has incrementally grown to the recently increased size of 6 m × 9 m. Since its beginning, the game is played with an orange golf ball and an overhead vision system. Robots are custom built according to the specifications of the league, currently to fit within a 180 mm diameter circle, no higher than 15 cm (Fig. 66.2).

The teams are allowed to use at least one camera overhead of the field. Robots have colored marks on their tops to enable visual identification and tracking. Off-board computation by each team uses the processed images to plan and then wirelessly communicate the team actions as the motion of the small robots on the field. The RoboCup SSL league offers challenges and significant contributions in: hardware design, colored-based real-time image processing (of the colored ball and colored marker identifiers of the robots), and in team strategy planning.

The RoboCup SSL robot hardware has evolved from the early simple and brittle robots in 1997 to the sophisticated, fast, robust, kicking, and dribbling, omnidirectional robot platforms of the current days. The hardware of the RoboCup SSL clearly pioneers small robot design, in contrast with all other much larger research robots in other applications. The league also significantly evolved in the vision processing and the playing strategy. Although the global view of the complete playing field is a clear advantage in capturing a complete view of the position of all the players and ball, it proved to be quite challenging to process in real time at 60 Hz, 10 fast moving robots, and a small orange

golf ball. As the league evolved, and some teams succeeded in devising vision processing algorithms, since 2010 such solutions became a shared vision system as part of the league setup that can be used by any team [66.34]. This [SSL](#) vision is available to all researchers and can be set to be used in other applications that may need global overhead perception. In terms of strategy, the teams aimed at passing and positioning well on the field since the beginning of the league. Both the capabilities of individual robots and teamwork became increasingly sophisticated and effective over the years, with the ability to dribble, to flat or chip kick, to perfectly navigate collision free at high speeds in a space crowded with opponents as dynamic obstacles, and to coordinate the team with effective defense, accurate passes, and precise aim at narrow openings of the goals.  [VIDEO 387](#) shows an example of the multi robot teamwork by the [CMU Dragons](#).

The ongoing research directions aim at learning the opponent strategy and responding to it. Through the common vision systems, all games are logged and now available for researchers to challenge learning algorithms with the complex positional, fast game data. Furthermore, the league aims at playing games of eleven players on a much larger field, also in ad-hoc teams, where the players are elements of different and previously unknown research teams.

Middle Size

The RoboCup middle-size league ([MSL](#)) started in the first RoboCup event in 1997. The league is set on a much larger field than the [SSL](#) one, initially of the size of 3 by three ping-pong tables. Currently, two [MSL](#) teams of six wheeled robots play on a 18 m × 12 m green carpeted field, with an official FIFA winter ball (orange).

[MSL](#) clearly differs from the [SSL](#) in its lack of centralized overhead perception and offboard computation. Each [MSL](#) robot is onboard fully autonomous, equipped with onboard sensors, computation, and actuation. Through wireless communication the robots can establish interteam cooperation and receive all referee commands. These two [SSL](#) and [MSL](#) leagues, were designed to offer frameworks for different robotics research interests in perception, planning, and mechanical robot design.

The [MSL](#) robots have evolved from a variety of initial experimental designs to the very effective, fast omnidirectional robots with creative kicking and defending actuation devices, in particular also in the goalie robots. At some point, robots had omnidirectional cameras that allowed each robot to compute the position of all the players on the field, for avoiding obstacles in its motion planning. Wireless communica-

tion allows for sharing state information and supports the implementation of cooperation strategies. Currently, teamwork accomplishments are based on the effective selection of robots to roles and attacking passes. In particular, the recent rules of the game force the robot to pass the ball in the opponents middle field before shooting to the goal. In this way, cooperation and passes have become a key feature for a successful team. The [MSL](#) goalie robots have been of special note, as teams build special hardware for them to allow for kicking and to effectively defend the long and well-aimed shots from the attackers. The [MSL](#) is compelling for the largest field size in RoboCup and robots of dimensions and speed that also allow humans to test play with the robots. Since RoboCup 2007, a team of volunteer members of the RoboCup Board of Trustees always plays a game against and with the [MSL](#) winning team. Such demonstrations are well appreciated by the competition audience and participants and provide evidence to the progress of the performances of the robots.

Standard Platform

The standard platform league started with the goal of providing a common hardware platform, so that the teams can focus their development on the algorithms and compare the performance of their solutions on the same hardware. Thus, in the standard platform league, all teams use identical robots, which happened to be legged robots. In the standard platform league all the challenges of the middle-size league are present (i.e., the robots operate onboard fully autonomously), but on a platform that requires a sophisticated motion control. The motion of the robot also affects perception and causes a greater uncertainty in the estimation of the environment and, thus, in basic capabilities such as ball tracking and localization of the robot in the field. The field evolved over the years: it is currently 6 m × 9 m and the game is played by two teams of five players with an orange ball.

The league started with the Sony AIBO (Fig. 66.3), in its early stages of development in 1998. After the first year demonstration, the league attracted several researchers, and underwent a substantial development both in terms of the platform, that evolved in three major revisions after the initial prototype, and in terms of the rules and requirements for the field. The AIBO robots had a very high number of actuators (16–18) to support 4-legged locomotion and body pose. At each revision, robustness of mechanical design, sensors, and computational power, steadily improved, thus, allowing to increase the size of the field (from 3 m × 4 m, to 4 m × 6 m) and to remove artificial landmarks, side barriers and strict requirements on the lighting.

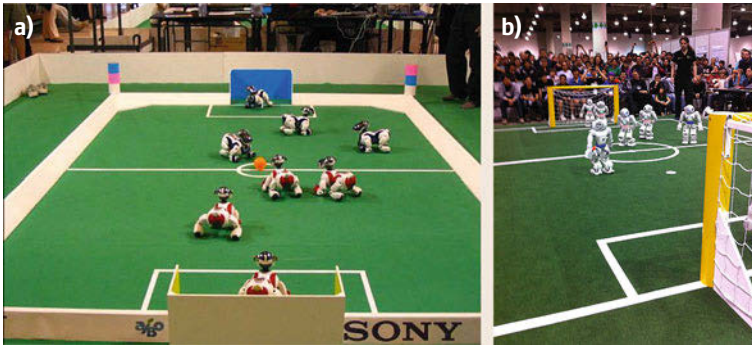


Fig. 66.3a,b Standard platform league: (a) AIBOs and (b) NAOs

Both the extremely advanced features of the platform and the availability of software developed by the RoboCup teams made the AIBO a very popular platform in research laboratories to test the performance of new legged locomotion techniques, perception localization and teamwork. As the performance of the robots improved over the years, not only the rules have evolved to meet new technical and scientific challenges, but also the games became very attractive for the general audience.

When Sony announced the discontinuation of the production of the AIBOs, RoboCup issued a Call for Platform that ended up with the choice of the current standard platform: the humanoid NAO by Aldebaran Robotics (Fig. 66.3), which has been used since 2008. The set up of the field did not change substantially; however, the biped platform required not only new locomotion, but also redesign of all the basic components. Again the platform evolved over the years, with corresponding changes of the field and rules. The current version of the NAO robot is 58 cm tall humanoid robot, with 25 degrees of freedom. The processing is provided by an Intel ATOM 1.6 GHz CPU (located in the head) that runs a Linux kernel and supports Aldebaran's proprietary middleware (NAOqi) and a second CPU (located in the torso). The platform is equipped with various communication devices, including voice synthesizer, LED lights, and two speakers, two cameras (one pointing toward the feet to control the kicking), tactile sensors and sonar rangefinders, Ethernet and Wi-Fi. The capabilities of the current platform allowed to enlarge the field to the current size (to $6\text{ m} \times 9\text{ m}$) and to remove from it all artificial features. Each game is played by five robots, plus an additional coaching robot outside the field. A section of the competition has recently started, where teams are formed by robots that are designed by different participants.

The adoption of a common platform has several advantages. First of all, the hardware is chosen so that the teams have a powerful, yet affordable robot, and speed up the development by sharing the same infrastructure.

Moreover, a standard hardware platform system makes a systematic comparison of different technical solutions more accurate. Finally, a common platform supports significantly community development that allows to reach the critical mass needed to develop complex robotic systems.

Humanoid

In the humanoid league, autonomous robots with a human-like body plan and human-like body senses play soccer against each other. The robots are designed and built by the competing teams, and include some of the best autonomous humanoid robots in the world.

The humanoid league was established in RoboCup 2002, Fukuoka. The later start, as compared with the other leagues is connected with the development of humanoid robots. The first demonstration of the early humanoid robots took place in RoboCup 2000 and Honda ASIMO first showed the ability to kick the ball, as a demonstration, in RoboCup 2002. Since then, the league started, initially addressing basic skills such as walking and kicking: the soccer game was limited to penalty kicks. In the first years of the league, very different robots were competing, but soon a separation in subleagues was gradually introduced, based on the size of the robots and on the constraints on the structure of the robot aiming to enforce dynamic walking. In 2005 the first two against two games were started in the smallest robot subleague. Since 2008, the game had three players in the kid-size and the league made a significant progress in terms of the number of participating teams and the capability of the hardware platforms. In the current setting, the robots of the humanoid league are divided into three size classes (Fig. 66.4): Kid-Size (30–60 cm height), TeenSize (90–120 cm), and AdultSize (130 cm and taller). In the KidSize soccer competition, teams have three players, in the TeenSize two players (keeper and forward) and in AdultSize soccer, a striker robot plays against a goal keeper robot in a dribble and kick competition. The size of the field is $4\text{ m} \times 6\text{ m}$ and the ball is of different size for

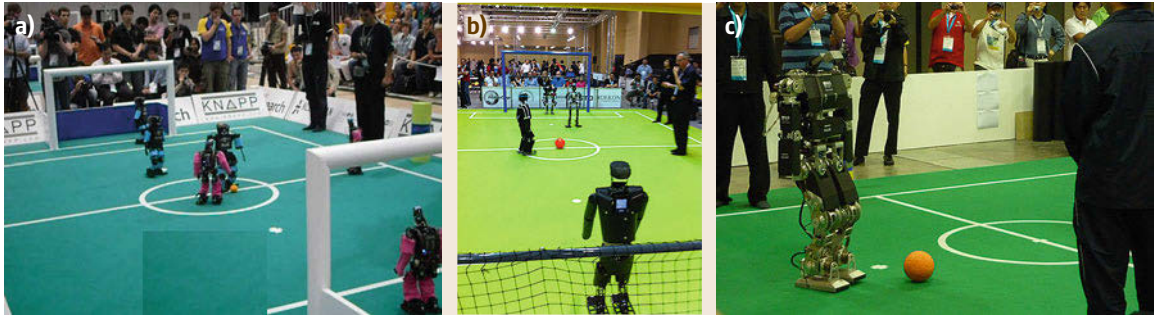


Fig.66.4a–c Humanoid Robots: (a) KidSize, (b) TeenSize, (c) AdultSize

the different subleagues. Unlike humanoid robots outside the Humanoid League, the task of perception and world modeling is not simplified by using nonhuman-like range sensors.

The challenges addressed by the Humanoid League embrace those arising in the realization of fully autonomous humanoid robots in the standard platform league; however, the overall design, including the hardware, makes it possible to aim at a richer range of solutions. More specifically, key issues addressed in the Humanoid League include dynamic walking, running, kicking the ball while maintaining balance, visual perception of the ball, other players, and the field, self-localization, and team play.

Conclusion

RoboCup is recognized as a major forum for research and education through competitions. The main international yearly event gathers about 200 teams, 1500 participants (not including Junior), and tens of thousands visitors. Regional events are also held worldwide, some of them of a size comparable to that of the main one. RoboCup is not only soccer, since it aims at fostering the development of new solutions also in applications that have a direct impact in our society: RoboCup Rescue, where robots compete to search and rescue in disaster scenarios, RoboCup@Home, where robots perform tasks that help people in daily life, Logistic League and the RoboCup@Work, where robots operate in industrial settings. Moreover, RoboCup provides a link to young generations through RoboCup Junior, a set of competitions specifically designed for the introduction of children to robotics and organized within the major event.

RoboCup has a profound impact on research. Researchers enter RoboCup competitions to validate their newly designed approaches to the broad spectrum of problems that arise from the grand goal of building teams of autonomous robots. Algorithms and robots are put to test in adversarial environments not previously seen, to show effective performance and ad-

vance the scientific and engineering state of the art in Robotics. There is a countless number of publications that present, in the most qualified Artificial Intelligence and Robotics venues, scientific contributions arising from the technical challenges tackled in RoboCup and validated through RoboCup games and platforms. The approaches and solutions developed in RoboCup have impacted many research areas. Particularly significant examples are the fields of humanoid robotics, multi-agents and multirobots, and performance metrics for Robotics.

RoboCup has brought significant contributions in education. The students, who form the teams, are the driving force of the effort to design and implement the components of rather complex integrated systems. Learning about cutting-edge solutions and experimenting them is a very effective way to develop creativity and design skills. Moreover, engineering within a team, in the framework of a competition, is a unique experience that goes far beyond the standard practice of academic curricula. In addition, RoboCup organized several Summer Schools, with a substantial hands-on component that has also been subsequently adopted in many other events. While some of the above features are not unique to RoboCup, the blending of ingredients and the environment provided by RoboCup have proven extremely rich, attractive and successful.

A few examples of particularly significant impacts that RoboCup had within our society are hinted below. Aldebaran Robotics NAO robot won RoboCup 2007 Open Call for a standard platform and afterward it has become popular through the standard platform league. Today NAO is deployed worldwide by research laboratories in robotics, becoming a commercial success. Kiva Systems are revolutionizing automation by using hundreds of mobile robots for storing, moving, and sorting inventory. In March 2012, Kiva Systems was acquired by Amazon. RoboCup and robot soccer were credited by Kiva's CEO for the success of the company. The search and rescue robot Quince, during the rescue oper-

ations in the Fukushima–Daiichi Nuclear Power Plant, could go up to the second to fifth floors in the nuclear reactor buildings. The robot was designed and evalu-

ated through RoboCup Rescue competitions, showing excellent mobility in comparison with the other competing robots.

66.4 Task-Oriented Competitions

In this section, we consider competitions that take their inspiration from common, but important tasks, currently undertaken by people. Competitions in this class tend to be focussed of dirty, dangerous and dull activities. Robotics of this kind is known as *Field Robotics* with robots typically having to operate in unstructured or semistructured environments, which often change over time.

The robots in these competitions are normally vehicles, such as ground vehicles (often cars), submersibles, or unmanned aerial vehicles. There is even a current high-profile competition to send a robot to the Moon, the Google Lunar X-Prize.

Unlike the competitions inspired by humans, task-oriented competitions are not driven by spectator experience. Spectators are welcomed at some of the competition events but not at all. Some are closed to competitors, organizers, and media only.

Task oriented competitions are held to drive innovation, raise the profile of a particular area of robotics, or to overcome nontechnical hurdles such as regulation and insurance which would otherwise stifle individual research projects. A competition is a more efficient method of addressing these issues than a collection of disparate research projects across the world. This type of competition also attracts professionals in robotics or soon-to-be professionals such as university students. They are hence a useful way to increase interest in industry participation and you will see major corporations with interests in the relevant technology and applications areas supporting or sponsoring a competition.

Unlike robot competitions inspired by sporting contests, task oriented competitions often happen as one-off events.

Task-based competitions in which the exact manner by which the task is to be accomplished is unknown, or significantly beyond the state of field, are often referred to as a *Challenge*. Challenges often have large cash prizes for the team that accomplishes the task reflecting the substantial investment of effort envisaged to claim the prize by the prize authority.

Ultimately even substantial cash prizes are almost always surpassed by the accumulated cost of the winning team's labour, equipment, donations by sponsors and overheads. Instead most participants are driven by prestige of conquering the challenge, *doing the im-*

possible and claiming the prize, or at least attempting to.

In recent years, the success of the robot competition format has lead to a number of contests including the MAGIC Competition [66.35], RoboCup Rescue [66.36], ELROB [66.37], and the AUVSI competitions [66.38].

A push to robot competitions to task-oriented robot challenges has also been given within the framework of scientific conferences such as AAAI and ICRA. Within this context, service robotics has also been a source of inspiration, addressing tasks such as serving drinks or preparing sushi. RoboCup@Home combines multiple challenges facing service robotics into a structured competition framework [66.39].

In the following sections, we examine at two representative task oriented competitions, the UAV challenge and the DARPA Challenge. While the robots differ significantly the drivers and approach to competition has many parallels.

66.4.1 Case Study: The UAV Challenge

Flying Robot Competitions

Competitions that encourage students to develop their skills with flying robots in exciting and challenging ways have been developed by universities and other research and education organizations since the early 1990s. One of the first, longest running and most successful flying robotics competitions is the International Aerial Robotics Competition (*IARC*) [66.40]. It was first held in 1991 at Georgia Institute of Technology. The aim of the competition is to push forward the state of the art in autonomy in flying robots. Teams are given challenges based on real-world scenarios, typically mock ups of disaster response or covert military style operations. A new challenge is announced once the current scenario is completed. Many scenarios take a number of years to be successfully demonstrated. Since 1991, *IARC* has seen six different competition scenarios. Nearly all of the scenarios involve interaction with ground elements meaning that the aerial robot must avoid obstacles and pick something up. This means that the successful platforms of *IARC* are nearly always rotary wing vehicles such as helicopters, ducted fan VTOL vehicles or in more recent year, multiro-

tor platforms. [IARC](#) is open to university-based teams from around the world. The past three [IARC](#) missions have involved the aerial robots having to navigate inside buildings as well as free-flying outdoors.

Another long running event is the International Micro Air Vehicles ([IMAV](#)) competition, which has been running since 1997 [66.41]. This competition focusses on very small unmanned aircraft operating either indoors, or in outdoor areas around an airfield or built environment. The [IMAV](#) events consist of a number of subevents, each aiming to push technology to solve specific research challenges, such as autonomy, perception, and flight dynamics. As reported in [66.41], the level of autonomy demanded to complete events has been increasing in recent years.

The Singapore Amazing Flying Machine Competition ([SAFMC](#)) is organized by Singapore's DSO National Laboratories and Science Centre Singapore and was first run in 2009 [66.42, 43]. It is typical of the type of competition event that is comprised of a number of different categories, from a basic radio-controlled flying competition to a category encouraging university level teams to design and build automated aircraft to navigate complex indoor obstacle course.

The UAV Challenge Outback Rescue is an international flying robot challenge that was first run in 2007 [66.44]. It is different to other competitions in that the aircraft have to be flown a considerable distance from the take-off and landing location. The competition revolves around a simulated scenario of a lost walker in the Australian outback with the start of the search area being 4 km from the take-off location and the furthest point of the search area being 6.5 km away. These distances require autonomous operation of the aircraft and reliable communications back to the ground stations – all things that stretch the capability of university and amateur teams [66.45, 46].

In 2013, the Wildlife Conservation UAV Challenge was launched [66.47]. This competition has a similar format to that of the UAV Challenge Outback Rescue, but is focussed on a scenario to find poachers of endangered animals in Africa. The aim of this challenge is to drive the cost down, and the reliability up, of small robot aircraft. The scoring system hence rewards teams heavily for low-cost designs, long duration capability and autonomy.

There are numerous other flying robot competitions run each year, including the USA-European micro UAV flight competition [66.48], the AUVSI Seafarer Annual Student UAS Competition [66.49], the International Universities MINI UAV Competition [66.50], the Chinese Robotics Competition which has a flying robot category [66.51], and the Annual Search and Rescue Cyber Physical Systems Challenge, where

teams build ground vehicles and the organizers provide a video feed from a UAV hovering above the indoor search area [66.52, 53]. A final category of flying robot competitions are the type held solely for participation within single universities and which are typically part of core course work in robotics or extension course work. A representative example of this type of internal university competition is given by *Schochmann* [66.54].

Motivation for Flying Robot Competitions

The stated aim of the longest running flying robot contest, International Aerial Robotics Competition, is to drive innovation [66.40], particularly in the area of autonomy. Many of the flying robot competitions and challenges of the past decades have focussed on this technology development or innovated uses of existing technology. However, not all flying robotics competitions and challenges are created for this reason alone, with some being linked to the education of high-school or university students who are studying robotics, while others are conceived to overcome nontechnologically based problems. There are a number of key issues that are potential inhibitors to the adoption of flying robots in the civilian context. In the mid-2000s, the general public considered flying robots as a military-only tool, being expensive and dangerous. This was largely due to a number of popular movies at the time depicting such things and high media interest in the use of unmanned aircraft by the USA in the Middle East conflicts of the time. In the 2010s, the public was concerned with privacy issues surrounding the use of drones (as they have become known in the media) and the fear that small unmanned aircraft could be misused by criminals or terrorists [66.55].

A second significant issue is that of airspace regulation. Flying robots will share the sky with manned aircraft. The airspace inhabited by manned aviation is highly regulated across the world. Before flying robots can be routinely used for civilian missions, both the airspace regulator of a particular country, and the general public in that country must be comfortable that flying robots will be as safe as current conventionally piloted aircraft. This issue is the single most significant hurdle to the adoption of unmanned aircraft in civilian airspace. A third issue, strongly related to the regulation and safety issue, revolves around the appropriate training, certification, and insurance of unmanned aircraft. Insurance companies work on precedence and past accident rates in order to determine risk and hence set insurance premiums. In a new industry, such as that of unmanned aircraft, with little data on which to base risk probabilities it is difficult for insurers to cover operators. Finally, as the unmanned aircraft industry grows, it will need people with the correct skills. These new

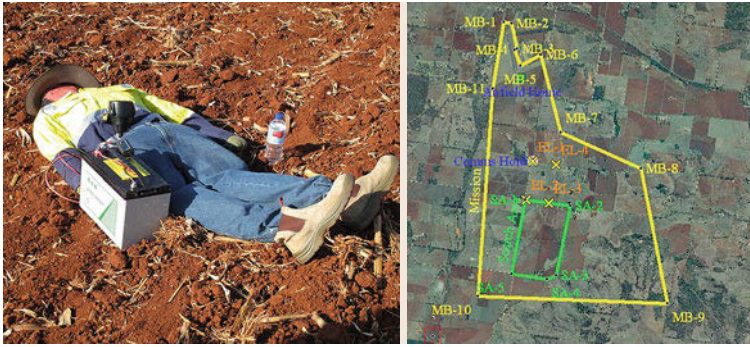


Fig. 66.5 (a) The aim of the Search and Rescue Challenge is to locate and drop a water bottle to a walker, Outback Joe. The mannequin wears bright clothes to help the teams find him using computer vision. (b) The course showing the Mission Boundary (yellow) and the Search Area (green). The airfield is at the top of the picture

Engineers, operators, technicians, and researchers will need to be trained in unmanned aircraft-specific areas of expertise.

The UAV Challenge Outback Rescue competition was created in Australia in 2007 [66.44] to attempt to simultaneously address all these major inhibitors to civilian use of flying robots. These broad aims meant that the targeted participants were from a wide cross-section of the community and included, the general public, high-school students, university students, radio-controlled aircraft hobbyists, the Australian aviation regulator (CASA), government, research institutes and universities, aerospace industry, and media.

Competition Formats and Challenges

The majority of flying robot competitions and challenges consist of multiple subevents or competitions, usually aimed at either different age groups of competitors or different skill levels. The level of complexity and the difficulty of the specific tasks set are set so that younger, less experienced students will almost always succeed to some degree and are hence competing against others like a sporting event. On the other hand, the events aimed at older or more experienced entrants are often deliberately conceived to be impossible to complete the first year that a team attempts it. These events are often referred to as Challenges while the easier events, where a team is expected to finish, are known as Competitions. A case in point is the UAV Challenge Outback Rescue that comprises a difficult Challenge, that is open to teams from around the world, and a high-school competition, that is far simpler, but still challenging, for high-school aged students. The two events share a common theme to encourage the high-school students to consider progressing to the Challenge in later years. The scenario for the UAV Challenge is that of locating a lost walker and dropping him a water bottle. Such a scenario is appealing to the general public, the media and the government.

The UAV Challenge Outback Rescue's major event is known as the Search and Rescue Challenge and was

unique in the world at the time it began in 2007 in that the competition took place over a large area of farmland and public roads. The lost walker was represented by a mannequin and was placed in a farmer's field approximately 4–6.5 km from a public airport in the regional town of Kingaroy in Queensland, Australia. The aim of the Search and Rescue Challenge was for a team to use their flying robot to find the lost walker (Fig. 66.5) and then drop him a water bottle. If a team managed those tasks, returned their aircraft safely to the airport and the water bottle landed intact less than 100 m from the bushwalker, they would win \$50 000. The Search and Rescue scenario was created to be as realistic as possible with competitors given a briefing document at the start of the day outlining where the lost walker was last seen and what he was wearing. Teams were under time pressure and given time limits on setup, mission time and pack up time. All of these restrictions were designed to make the scenario as close to a real rescue as it could be. Teams were evaluated on their mission performance and on their documentation meaning that even if no team completed the mission, their could still be a points winner, who would be awarded the title of First Place and receive a smaller cash prize. This is typical of Challenge-type events where a number of years may go by without a team completing the main challenge. Another typical feature of this event it is that it is not set up as a spectator event because the nature of the Challenge makes it almost impossible to follow if you are not directly involved in the action.

The high-school competition of the UAV Challenge Outback Rescue is known as the Airborne Delivery Challenge as takes place on the airport site and within the airport boundary. This competition is therefore set up to be a spectator friendly event. This scenario required high-school students to pilot their unmanned aircraft over the same walker, who is located in sight of the general public close to the air-side fence. Teams are required to drop a package to the walker, but the pilot cannot select when to make the drop. Instead, a second team member located in a tent and with no line of sight

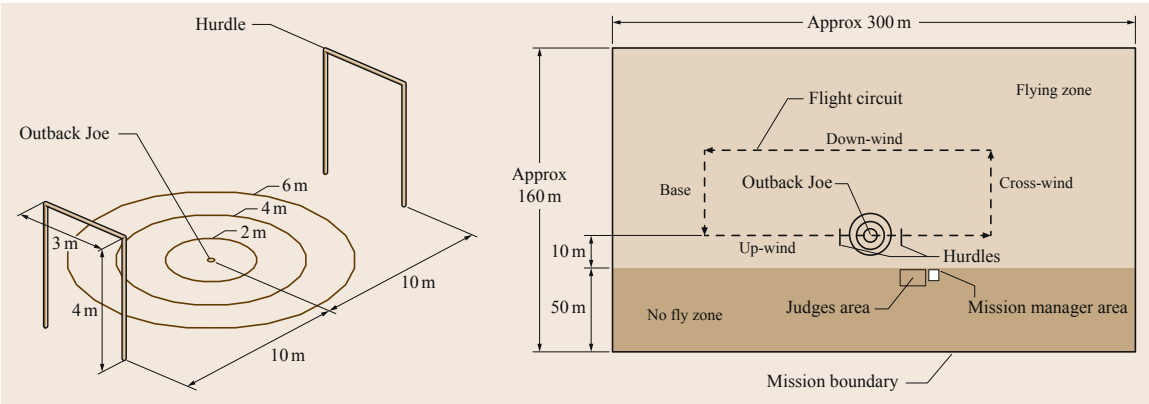


Fig. 66.6 The Airborne Delivery Challenge course showing the hurdles and the flying zone

to the bushwalker has to make the drop (Fig. 66.6). The aim of this scenario is to force teams to use some technology to help assess when to drop the package. Many teams are successful and a points system determines the winner.

Qualification and Precompetition Testing
Some flying robot competitions and challenges have a qualification element to them which means that teams must demonstrate a certain level of competence prior to the actual event. This requirement implies that many of these competitions can be considered to be much longer in duration than the relatively short events that take place on the competition days at the end. The UAV Challenge Outback Rescue for example, takes place over a long time period leading up to the event. Since 2007, the Search and Rescue Challenge has been held both over a single year and as a 2-year long campaign. In both forms of the event, the high-school and the international open event, teams must provide documentation to the organizers to demonstrate their competence, their progress, and their treatment of safety. Safety is the priority issue for the organizers and the teams at flying robot competitions and challenges. In the case of true UAV Challenge, the unmanned aircraft are operated over farmland, over public roads and close to the general public who come to spectate (Fig. 66.5).

Teams first register for the UAV Challenge and are then asked to provide documentation, known as Deliverables. The first deliverable must show a basic system design and an analysis of risk. The second deliverable must show the final design and adherence to the mandatory safety features of the UAV system. For the 2-year long version of the Search and Rescue Challenge, a third deliverable was added where teams were asked to show documented evidence of at least 5 h of autonomous flight of their unmanned aircraft. This final set of documentation was introduced

to ensure that only teams that were capable of actually flying for a sustained period of time in the search range qualified for the event. By its nature, the qualification process significantly reduces the size of the field as a competition or challenge progresses. For example, in 2011–2012, 68 teams registered to take part in the Search and Rescue Challenge, with 61 submitting a the first deliverable document. Of those, 53 teams from ten countries, qualified to continue. At the second deliverable stage, 23 teams qualified to continue to the final deliverable phase where nine teams qualified and were invited to the actual flying event. Between that announcement and the event, four of the nine teams pulled out due to crashes during testing and other issues leaving just five teams to compete during the event (Fig. 66.7,66.8).

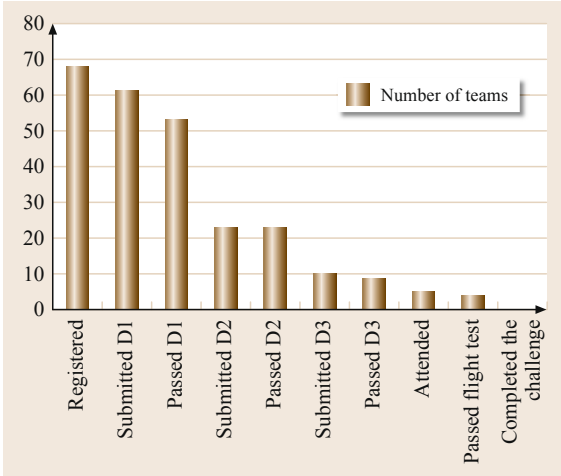


Fig. 66.7 The number of teams declines as the UAV Challenge progresses. In 2011–2012, 68 teams registered and throughout the 18 months of the competition teams dropped away leaving only 5 at the event

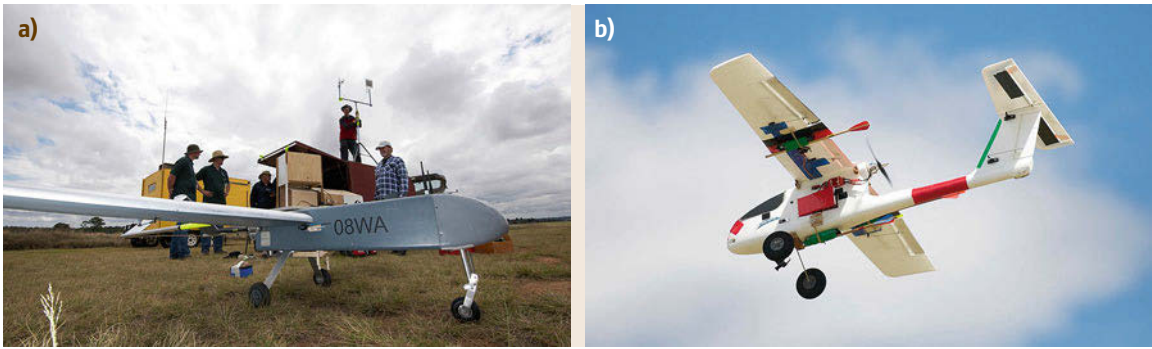


Fig.66.8a,b (a) First place team from the 2012 Search and Rescue Challenge, Canberra UAV. (b) Winners of the 2012 Airborne Delivery Challenge, MUROC Hawks

It is common at flying robot events to test teams prior to the actual competition flights. In the UAV Challenge Search and Rescue event, the final phase of qualification involves the teams being tested or scrutineered. The scrutineering process aims to test both the safety systems of the unmanned aircraft, the supporting systems and the team themselves, including any safety pilots. The scrutineering is undertaken by industry professionals and consists of a static scrutineering test where the team is interviewed, the aircraft and systems inspected and the flight termination tested. Teams that pass scrutineering are then invited to fly their aircraft within the boundary of the airport where the ability of the team to fly autonomous is tested. Only teams that pass this final hurdle are invited to launch a search and rescue mission and compete for the grand prize. In 2011–2012 Search and Rescue Challenge, four teams passed the final scrutineering tests meaning that just over 5% of teams that originally registered qualified for the final mission. In comparison in the 2013–2014 event, this qualification rate increased to 17%.

Regulations and Safety

Many flying robot competitions are carried out indoors. As well as guaranteeing that bad weather will not cause problems for the event, a major reason to hold a competition indoors is that in most countries, this means that the official airspace regulator does not need to be involved in any way. Unmanned aircraft flown indoors pose no threat to manned aviation flying above. However, a number of high-profile flying robot competitions do take place outdoors, including IARC and the UAV Challenge Outback Rescue. The latter event must be undertaken within the specific regulations for the operation of unmanned aircraft in Australia. These regulations were launched in 2002 by Australia's civilian air regulator, the Civil Aviation Safety Authority (CASA) and are known as CASR Part 101. The reg-

ulations outline the operating rules for three defined classes of unmanned aircraft, micro UAS under 100 g, small UAS 100 g to 150 kg and large UAS 150 kg and above. The rules of the UAV Challenge dictate that the competing team's cannot enter an aircraft in the large UAS class. Normal commercial operation of small UAS would require the operating business to obtain an Operators Certificate from CASA. However, the competition is classified Sport and Recreation by CASA and hence an Operator Certificate is not required. CASA treats the UAV Challenge organizers as the body accountable for the safe conduct of the event and adherence to the relevant regulations. The UAV Challenge organizers have developed the event rules to specifically meet the requirements of the regulations and to hence ensure that if a team is following the rules, they are in turn not in breach of the regulations. Further to this, the organizers have also developed a detailed Policy and Procedures manual that outlines how the UAV Challenge will be conducted to ensure safety and adherence to the regulations by the organizers themselves. Developing the manual and the supporting rules has been a major activity of the organizing committees over the years that the event has been run and is a significant output from the whole UAV Challenge activity.

What makes the UAV Challenge different to many other unmanned aircraft competitions is that because the event takes place largely beyond visual range of the team's ground controllers, and an aircraft could be up to 7 km from the ground station, there is a higher potential for a so-called fly-away than there is during the more common style of events where the flying takes place in close proximity to the ground station. A fly-away is where the aircraft flies out of the designated competition area and cannot be commanded to return. Such an incident could be seen as a major setback to the developing unmanned aircraft industry. In the first 2 years of the UAV Challenge, the mitigation for fly-away was to mandate the use of a flight

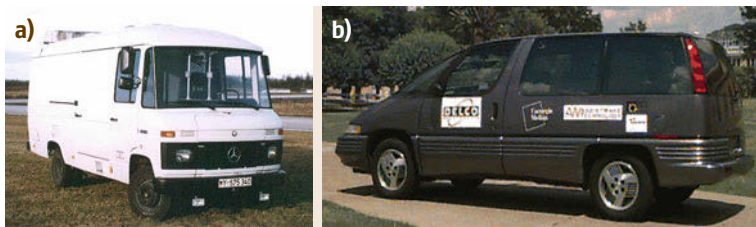


Fig.66.9a,b DARPA grand challenge vehicle ancestry. Pioneering autonomous vehicles of 1980s, 1990s. (a) 1985: UBM's Vamors. (b) 1995: CMU's Navlab 5 used for the *No Hands Across America* trial

termination mode whereby any aircraft that crossed the defined competition boundary or lost contact with the ground station had to automatically perform a fast dive into the ground. All aircrafts were tested during the scrutineering sessions to ensure that this behavior was built into the systems. Since, 2010, the requirements have kept step with the more common industry approach to lost communications and teams are now allowed to deploy aircraft that will automatically return to a predetermined location in the competition area should communications be lost between the ground station and the aircraft. The requirement to automatically terminate a flight on competition boundary crossing remains and is still the last line of defence against a fly away. Many teams have lost aircraft during the testing and development of their flight termination systems and this requirement is still one of the most challenging of the UAV Challenge.

Organization and Sponsorship

The nature of flying robot competitions and challenges often require large teams of organizers with complementary skills. For example, the UAV Challenge Outback Rescue is organized and run by two committees whose members typically come from the organizations that provide support for the event. The first committee is the Steering Committee and runs all nontechnical aspects of the UAV Challenge event such as equipment hire, securing sponsorship, liaising with local government and carrying out event communications and media activities. This committee is also responsible for the event finances. The second committee is the Technical Committee. This committee is responsible for developing and releasing the rules for the UAV Challenge. The committee also liaises with air regulator and works with the UAV Challenge Steering Committee on the event organization. At the event, the Technical Committee is responsible for the airside part of the UAV Challenge which includes selection of the technical team that runs all technical issues relating to the event, scrutineering of the teams, the supervision and scheduling of the actual competition flights and the coordination of aerodrome activities during the event times. The Technical Committee meets regularly throughout the year with initial meetings held to formulate the

rules and incorporate lessons learned from the previous year. The Technical Committee reports to the Steering Committee.

Each time the UAV Challenge is run, sponsors are sought to cover the costs of the prize money and the hire of facilities. The organizations that come together to run the UAV Challenge provide the time of their staff as an in-kind contribution. The total budget of a UAV Challenge is approximately \$125 000 plus the staff time of the organizers. It is hence a considerable undertaking and requires a significant number of sponsors to break even. The UAV Challenge has been well supported over the years, attracting the sponsorship of major aviation companies such as Boeing and Lockheed Martin as well as unmanned aircraft companies such as Insitu. The safety regulator, CASA, has also sponsored the event.

66.4.2 Case Study: The DARPA Challenges

In 2001, the United States Congress challenged the Department of Defence with the following mandate [66.56]:

It shall be a goal of the Armed Forces to achieve the fielding of unmanned, remotely controlled technology such that by 2015, one-third of the operational ground combat vehicles of the Armed Forces are unmanned.

In response, a little over a year later, the Defense Advanced Research Projects Agency (DARPA), the primary research and development organization for the United States Department of Defense, announced that there would be a race.

The race, to be titled the *DARPA grand challenge* was to drive a robot car 300 miles from Los Angeles to Las Vegas in the fastest time to claim the \$1-million dollar prize [66.57].

The aim of the DARPA grand challenge was to reinvigorate and extend autonomous vehicle technologies from the 1980s and 1990s to future defense vehicles. Initiatives such as the Universität der Bundeswehr Munich (UBM)'s Vamp/Vamors vehicles, University of Parma and Carnegie Mellon University's NavLab's research program (shown in Fig. 66.9) had demonstrated

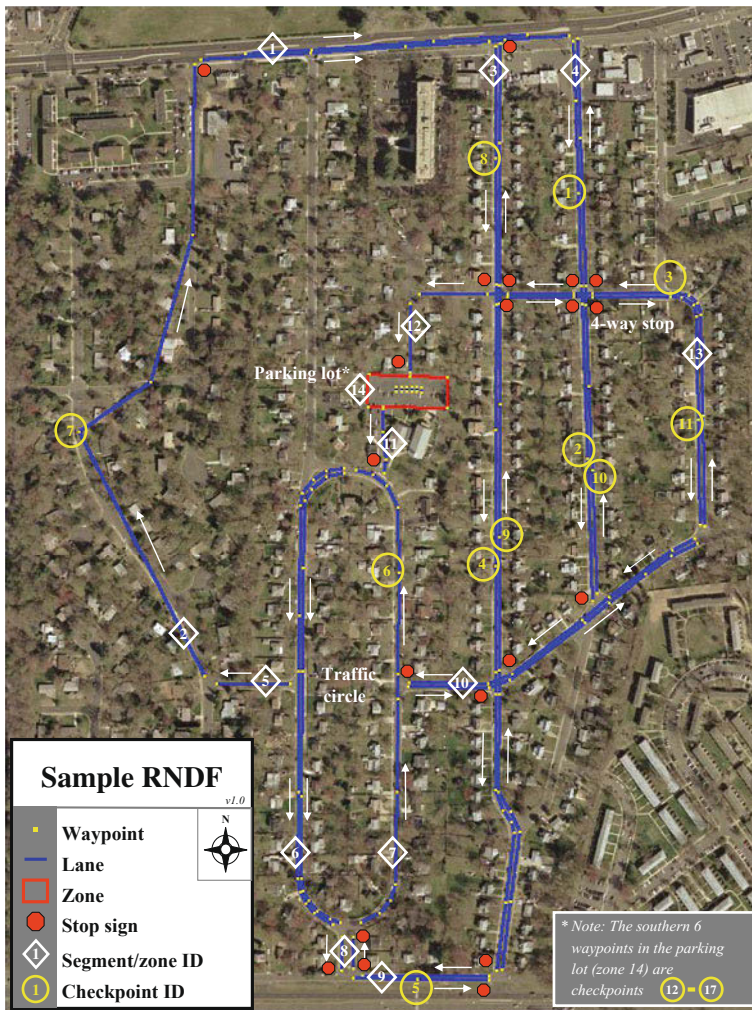


Fig. 66.10 A sample route network definition file (RNDF) provided by DARPA for the 2007 Challenge (overlaid on aerial imagery)

impressive feats of road vehicle autonomy. Trials across thousands of highway kilometres had demonstrated lane keeping, obstacle avoidance and even automatic overtaking (passing) [66.58–60].

The problem was, close to a decade later, the capability of current technology full-sized, fully autonomous vehicles was unknown. The impressive trials of the late 1980s and 1990s concentrated on highway driving where the primary task was computer vision-based lane keeping. There were indoor and outdoor robots navigating through challenging *obstacle field* style environments [66.61, 62]. There were also teleoperated vehicles already in use by the defense forces. The question was, given computation power tracking with Moore's law over the intervening years and many other advances (such as the use of LIDAR), what would robot car be capable of?

DARPA aimed to [66.63]:

- Demonstrate an autonomous vehicle able to travel over rugged terrain at militarily relevant speeds and distances.
- Accelerate autonomous ground vehicle technology development in the areas of sensors, navigation, control algorithms, hardware systems, and systems integration.
- Attract and energize a wide community of participants not previously associated with Department of Defense programs or projects to bring fresh insights to the autonomous vehicle problem.

Potential participants were drawn to the challenge. Many participants could also see the potential for related technologies in the automotive industry and for road safety [66.64].

Teams would develop a vehicle that could follow a simple route across a course representing typical ter-

rain encountered by defense vehicles. The route map would be a set of paths specified by GPS way-points. The vehicle would be then given a list of destinations in the map and instructed to drive to each location. A typical route map is shown in Fig. 66.10 overlaid on the satellite image.

For this first competition, as for those that followed, the rules stated that the robot must be a fully autonomous and unmanned ground vehicle. Each vehicle was fitted with a wireless remote E-stop to bring the vehicle to a halt. On the base vehicle was added sensing, processing, and control. Some vehicles were built from the ground up. Most teams fit actuators to the manual controls of an existing vehicle, some built upon disability aid kits fitted to the vehicle. A couple teams were able to tie into existing *by-wire* capabilities of the vehicle, a notable example being Victor Tango's 2007 challenge entry *Odin* [66.65]. In addition to GPS, vehicles needed to have sensing for obstacle avoidance, in which LIDAR sensors dominated. As the vehicles were to be completely autonomous, all sensor processing, and control had to be done on-board so a certain amount of computer power was incorporated. Then the practicalities would necessitate other devices such as power generators and additional air conditioning, if required. The general anatomy of a DARPA grand challenge vehicle is illustrated at Fig. 66.11. This vehicle, from the 2007 DARPA Urban Challenge, was at the upper end of the spectrum for additional equipment with LIDAR, video cameras and automotive radar, as well as a generator and supplementary air conditioning required for a blade server computer housed in the rear compartment [66.66].

2004 DARPA Grand Challenge
DARPA hired *Score international*, an off-road race organizer, to develop the course [66.67]. A 142-mile course was laid out through the Mojave Desert. The competition was structured as a time trial to complete the course in the shortest time under 10 h. One hundred and six teams applied.

In March 2004, 25 teams turned up for the competition. In the days leading up to the race a qualifier, inspection and demonstration (QID) round was conducted. This event was primarily to verify that the vehicles were fit to compete and capable of operating safely. By race day, the 15th of March 2004, a field of 15 vehicles had qualified and were ready to race.

As stated earlier, a primary goal of the competition was to gauge the state the art in the field. Steep elevation, blind turns, and sheer drops adjacent to the course were included to challenge the vehicles. While the degree of difficulty was low by human off-road driving standards, the course was designed to be in-

teresting and make for a good competition [66.67]. Expecting something akin to human driven competition, DARPA even advised the media to set up at the finishing line where the action was expected to take place [66.68].

However, the course and the autonomous driving problem proved too difficult for the robot vehicles. No vehicle made it beyond the first seven miles of the course. After a promising start the vehicles soon became stuck or had to be disabled by a safety official after deviating from the course. One vehicle's wheel caught on fire, another flipped around a bend another began circling around in the starting chute [66.69].

Inexperience was the chief cause of failure on the 2004 contest. The new nature of the challenge and the stretch of mobile robotics to a full-sized off-road vehicle introduced too many complications for the robots systems.

The challenge stood unbeaten, the prize money remained unclaimed. The real world complications and the size of the challenge were now apparent. Also apparent, however, was the curiosity sparked within the research community and the general public.

Three months after the first competition, DARPA announced the 2005 DARPA Grand Challenge – a re-run of the event, this time for a \$2-million dollar prize.

2005 DARPA Grand Challenge
With a slightly longer lead time, DARPA held a participants' conference and conducted site visits to each team to gauge progress. At the participants' conference team representatives and DARPA officials discussed the draft race rules, clarifying rule interpretations and technical specifications. Out of 195 entrants, DARPA officials flew out to attend 118 site visits.

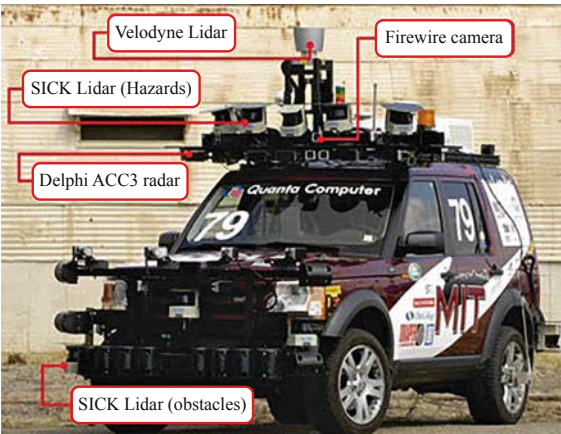


Fig. 66.11 Anatomy of a DARPA grand challenge vehicle. 2007 DARPA Urban Challenge entrant MIT's *Talos* was on the upper end of the additional equipment spectrum

From the site visits 43 teams were selected to participate in the national qualifying event (NQE). During the qualifying event, which was twice as long as 2004, the teams had to complete a miniature version of the course which was created at the California Speedway (Fontana, California, Fig. 66.12).

By race day, 23 robots were selected as starters in the race. The vehicles queued up to start at 5-min intervals. DARPA officials paused slow-moving vehicles to permit faster robots to pass.

The difference between the 2004 and 2005 competitions was stark. Eighteen months on from the first competition, five robots drove 132 miles across the Mojave Desert to complete the course [66.63].

The race winner *Stanley*, from the Stanford Racing team, claimed the prize – completing the course in 6 h, 53 min and 58 s (Fig. 66.13) [66.70]. Second and third places were taken by robots from Carnegie Mellon University (CMU) teams: *Red Team* and *Red Team Too* [66.63]. *Kat-5* from Team Gray came forth, a remarkable achievement from a team founded by Louisianan insurance executives. And last, but not least, the 16-ton *TerraMax* truck by the Ochkocho Truck Corporation which completed the course the following day after spending the night *paused* on the course.



Fig. 66.12 Miniature version of the course which was created at the California Speedway



Fig. 66.13 Winner of the 2005 grand challenge Stanford Racing's robot *Stanley*

It was a trail blazing event which captivated the public with news images of unoccupied race vehicles kicking up dust as they drove across the Mojave desert sand.

During the qualifiers and the race some common weaknesses were also identified. The vehicles required GPS for navigation as all the course information were given GPS coordinates, however the vehicles also appeared to be overly reliant on a strong, correct, GPS signal. During the race vehicles drove under high voltage power lines which caused GPS loss. Vehicles deviated from the course or even crashed due to loss or multipath signals. Several robots were also able to make significant progress *driving blind* after sensor failures meant that local obstacle avoidance was no longer functioning correctly.

In 2006, DARPA announced the next grand challenge, the *DARPA Urban Challenge*. The contest this time required fully autonomous vehicles to drive on an urban street network.

2007 DARPA Urban Challenge

In the *DARPA Urban Challenge*, robot vehicles were to follow the Californian driver's handbook. Unlike the previous challenge where vehicles were not intentionally presented with moving obstacles (other robots were paused when they became too close to each other) the aim of the contest was to test the vehicles' ability to drive in traffic. This time vehicles were expected to keep to lanes, queue in traffic, park, merge, pass, and even observe intersection precedence (i. e., yield to cars already at an intersection) [66.71].

In a new element in the 2007 Challenge, DARPA introduced seed funding of up to \$1-million dollars for per team for 11 teams based on a competitive application process to bootstrap the cost of development of the increasingly complex robot platform. The seed funding attracted new entrants to the competition in line with DARPA's aim to attract a wide community of participants [66.72].

On November 3, 2007, the urban challenge event (xUCE) was held in Victorville, California. This event set loose, simultaneously, for the first time, 11 full-size autonomous vehicles on a closed course (Fig. 66.14).

The UCE was held on a closed course within the decommissioned George air-force base. The course was predominantly the street network of the residential zone of the former base with several graded dirt roads added for the competition. The contest was cast as a race against time to complete three missions. The missions were different from each team but were designed to require each team to drive 60 miles to finish the race. Penalties for erroneous or dangerous behavior were also converted into time penalties.

Most roads were paved with a single lane in each direction as typical for a suburban street. A couple of roads had two lanes of traffic in each direction to simulate an arterial road or highway. One road, in the southeastern corner of the network, was a raised dirt road constructed especially for the event.

This time all 11 qualifying robots were allowed to interact in the UCE course simultaneously, with additional traffic vehicles driven by professional drivers. For the third time, like anxious parents, the researchers manned the fences helpless as the robots, whose development had consumed the past 12 months of their lives, one by one, drove away. There were some tense moments and even a fender bender [66.66, 73]. However, powering through the mission objectives with a driving style described as *a soccer mom with some place to be* [66.74], CMU's Tartan racing's robot *Boss* (Fig. 66.15), crossed the finish line [66.73] to claim the prize. 2005 winning team Stanford Racing came second with *Junior* while team Victor Tango's robot *Odin* secured third place. Six robots completed the race [66.72].

Review

DARPA endorses the use of competitions to cause paradigm shifting advances in science and technology. As stated DARPA's 2007 Fiscal year report [66.72]:



Fig. 66.14 DARPA starters



Fig. 66.15 Tartan racing's robot *Boss* crossing the finishing line

The program achieved its program goals and stimulated interest in the programs and projects of interest to the DoD Science and Technology (S&T) community. It was successful in attracting considerable joint investment by the participants and their sponsors, effectively leveraging Government investment in the program. The technical challenge was carefully defined and staged to bring coherence to the community and increase the chance for cross-fertilization among competing groups. The solicitation and qualification process was successful in attracting a large pool of strong teams with participation from the defense industry, automotive industry, academia, as well as a number of smaller organizations. This investment in expanding the community will continue to pay dividends as DoD benefits from a strengthened commercial sector autonomous vehicle technical community. The program has been successful in attracting many young people to work on S&T problems in areas affecting national security, and benefits are expected to accrue for many years as this group enters the work force.

Although DARPA's approach may raise the question of whether research initiated by the competitions should be supported beyond competition, DARPA's view is that its role is to kick start ground breaking research not bring it to completion [66.1]. They encourage research teams and commercial organizations to team up to bring the technology to market for defense vehicles [66.72].

Velodyne LIDAR, a dominant sensing technology in the 2007 grand challenge, was developed with road safety potential in mind by Team DAD from the 2005 DARPA grand challenge [66.75]. The invention is a good example of the technological pull DARPA was wanting to achieve with the competition.

Another direct outcome of the competitions is the Google self-driving car project, which is based on the research and researchers from grand challenge teams [66.76]. Many vehicle manufacturers, such as Ford, General Motors, Volkswagen, and Toyota among others, have either entered the competition, partnered with teams or employ competition alumni to continue to develop and apply related technologies to road safety [66.64, 70, 72].

The DARPA Robotics Challenge

Buoyed by the success of the grand challenges, DARPA now hopes to accelerate the development of humanoid rescue robotics. In April, 2012 DARPA proposed the DARPA robotics challenge. The Challenge is to develop an adaptable ground robot capable of completing tasks in a dangerous and degraded environments, using hand



Fig. 66.16 DARPA robotics challenge conceptual illustration

tools to driving vehicles for disaster relief operations (as illustrated in Fig. 66.16 [66.77].

Similar to the first grand challenge, an ambitious goal has been set to inspire and stretch the state of the art.

Though it is important to note that the new robotics challenge is a separate research program from the previous grand challenges, some best practices and lessons learned from the previous Challenges have been adopted. Entrants are divided into four tracks. Tracks A and D compete to develop hardware and software of a complete robotic system. Tracks B and C compete to develop software first to run on a common simulated robot. Tracks B and C will then compete in a virtual competition. In 2014, successful Track B and C teams will be able to develop and deploy the software to a common robot platform provided by DARPA. The entrants can also apply for seed funding (similar to the), which differentiates teams between Tracks A and B, who have DARPA seed funding, and C and D who are self-funded [66.77].

The idea of using a common platform across teams and a simulator-based challenge addresses the observation that successful teams in the 2007 challenge had arrived upon similar sensors and sensor configurations. So a future challenge could remove the significant hardware development burden by allowing teams to compete on a common platform. The motivation is to once again broaden field of participants [66.77].

The new robotics challenge also introduces access to a remote human supervisor. Previous challenges were strictly fully autonomous. A criticism had been that due to the extreme lack of contextual information available

to most robotic systems, simple ambiguities that arise can impede a robot unnecessarily if a supervisor can correct the problem. The lack of supervisory control meant that in previous challenges vehicles would appear *overly cautious*.

For example, many vehicles in the 2004 Challenge were incapacitated by trivial problems such as the robot misjudging which side of a road boundary they were actually on. Full autonomy should be the ultimate aim; however, allowing limited supervisory contact would have permitted the 2004 contest to continue allowing more trial time for teams.

Conclusion

DARPA never aimed to create the ultimate autonomous vehicle. The true aim of the competition was to advance the science and technology research and education underpinning the original Congressional mandate on autonomous vehicles.

Of course, the exercise has come with considerable cost. From the 2007 Fiscal report [66.72] the true dollar cost to DARPA of the competition came in at around 25 million dollars. Three and a half million dollars were paid directly to the winning teams as prize money. A further \$11 million was paid in Track A grants to teams, with the remaining \$10.5 million was used to host the participants' conference, site visits, qualifying round, and stage the final event.

Notwithstanding these costs and the necessarily limited nature of these competitions – which create an artificial environment to focus a broad group of experimenters on a common goal, for a given period of time – they have brought clear benefits for DARPA, and the field of robotics.

Regardless of the percentage of autonomous vehicles fielded by the Department of Defense in 2015, the experience shared by participants from: research institutions, car manufacturers, defense contractors, technology companies, schools, a loud speaker company [66.75] and even insurance executives [66.78] to attempt the challenge of creating a full size, fully autonomous, self-driving car has gathered the field for an even greater race. The race between companies such as Google, Mercedes Benz, Toyota and their technology suppliers to bring these vehicles to market not only for defense vehicles but for all road vehicles.

An outcome beyond the dreams of the forward thinkers in the 2001 Congress.

66.5 Conclusion and Further Reading

In this chapter, we have discussed several types of robot competitions highlighting their impact on research and education. Here we summarize the manifold impacts of competitions as well as the major issues that need to be addressed to design and run them.

Robotics competitions with ambitious aims can provide significant breakthroughs in the development of science and technology.

To this end, competition models based on one time challenges have the advantage of being able to headline a fresh new goal. The drawback for the organizer and participants is the significant effort to build systems and infrastructure that may be too specialized to be used after the competition for subsequent challenges. On the other hand, challenges that are developed across the years can benefit from a continuous development, as long as they suitably build on yearly achievements, without loss of focus on the long-term roadmaps. The two approaches as outlined in the case studies demonstrate the merit of both as well as the unquestionable impact on science and technology.

Robots are complex systems composed of many mechanical, electrical, software, and algorithmic components and as such are hard to test and compare. In isolation a test can be derived to evaluate some components or subcomponents. For example, one can test the degrees of freedom of a mechanical design, or the bandwidth and latency of a data bus. Image processing and mapping algorithm development have made great strides using shared datasets to compare results. The performance of a robot system as a whole would often fall back to a qualitative assessment presented as a video accompanied by the encouraging words of the researcher. Competitions provide the motivation and the forum for robotics researchers to undertake the significant effort (in time, compatibility, and transportation) to develop and validate innovative solutions on complex systems under controlled conditions.

Robot competitions have a positive impact on robotics research groups in that the team work requirement within and between groups means that a better standard of core software is achieved across the group. Good tools in terms of software libraries and best practice by the more experienced software engineers in a group are often adopted across the team enabling algorithms to make it onto robot hardware sooner. To this end, it is critical that competitions support the sharing of solutions and tools, by developing community infrastructure and resources. This kind of gently enforced openness keeps competitions competitive, fosters interactivity between teams and encourages diversity of participants by minimising the barriers to entry.

Robot competitions can play a tremendous role in education. They are attractive to students and teachers, while providing an interdisciplinary framework to support the development of several types of technical skills, including teamwork. Maintaining a good balance between competing and learning becomes a major concern when the focus of the competition is education. In international competitions with younger students, differences in culture and language need to be carefully taken into consideration to maintain fairness and inclusiveness.

Last, but not least, robot competitions have a significant impact on public opinion and the public understanding of the science and technology. Simple distinctions such as autonomous versus teleoperated robotics are often mistaken or overlooked by the news media and the public. Human-inspired competitions have attracted many spectators and the attention of the media, and they certainly contribute to make scientific progress more accessible, through the language of sports. Grand challenges, such as the [DARPA Challenges](#) have been extensively covered by the media, thus, contributing, although from a different perspective to disseminate the awareness on the progress of robotics in the society.

The aforementioned outcomes do not come without a significant effort. A successful competition must clearly define a target participation and suitably support it, by making the entry level accessible to a large number of participants. The technical challenge needs to be appropriately compelling and attractive; moreover, the competition setting must ensure that winning is achieved through innovation and scientific progress. This is achieved by designing the requirements on the robots and on the competition scenario as well as through a well-designed performance assessment.

The organization of competitions also comes with formidable challenges: logistics for transporting robots and teams, venue and infrastructure for the competition event, safety of participants and spectators. The financing and administration, often underestimated, also requires substantial preplanning, know-how, and resources.

This notwithstanding, we expect the use of competitions to motivate, educate, and foster research innovation only to increase in coming years as competition has proven to be a particularly useful tool for robotics research.

66.5.1 Further Reading

Research results of robot competitions are often accumulated into a journal special issue. The reader is

encouraged to explore the articles as they are often approachable and can include interesting details of events during the contests. For the **DARPA** grand challenge the reader may refer to the *Journal of Field Robotics* Volume 23 (2006) Issues 8 and 9 or the *Springer Tracts in Advanced Robotics* Volume 36. For the **DARPA** the reader may refer to the *Journal of Field Robotics* Vol-

ume 25 (2008) Issues 8 and 9 or the *Springer Tracts in Advanced Robotics* Volume 56. In future, similar special issues are likely to be available on the **DARPA** robotics challenge.

US Innovation Programs [66.79] is interesting review on the broader discussion of competitions in funding science and technology research.

Video-References

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Robots and Humans covers some of the most recent advances concerned with human–robot interaction, ranging from designing biologically inspired robots, to programming and safety issues for human–robot interaction, and ethical issue brought forth by robotics. Our field’s future vision for technology is the leap from personal computers to personal robots, in a world where robots exist pervasively and work side by side with humans. Over the past 50 years we have made great strides in robotics, as the previous parts of this Handbook show. However, there are still new capabilities that need to be developed and existing capabilities that need to be improved to create a world in which robots and humans work together. Robot bodies should be easily integrated into our living environments. Robots should be safe to be around. Robots should take commands from human users easily. Robots should be functionally capable. Robots should engage humans to help mitigate error states and task uncertainties. Meeting these challenges will bring robots closer to our vision of pervasive robotics.

The topics in **Part G** are essential for creating robots that operate in human-centered environments. The chapters cover organically human-centered and life-like robots and include hardware design, control (of locomotion, manipulation, and interaction), perception, user interfaces, and social and ethical implications for robotics. As such, Part G builds on all of the Handbook’s previous parts. The connection with the chapters in Robot Foundations (Part A) and Robot Structures (Part B), particularly Mechanisms and Actuation (Chap. 4), Sensing and Estimation (Chap. 5), Motion Planning (Chap. 7), Robotics Systems Architectures and Programming (Chap. 12), AI Reasoning Methods for Robotics (Chap. 14), Robot Hands (Chap. 19), Limbed Systems (Chap. 17), Modular Robots (Chap. 22) and Wheeled Robots (Chap. 24) are essential. There is also an important dependency on Sensing and Perception (Part C), Manipulation and Interfaces (Part D), and Moving in the Environment (Part E) as these chapters cover some of the basic algorithms and technologies required by robots operating in human-centered environments.

Today’s approach to computation has progressed naturally from desktop computing, to mobile computing, to pervasive computing, ultimately leading to computation for interaction with the physical world. In other words, Part G of the Handbook on Robotics presents a snapshot of the field’s advances for creating machines in our own image that are smart and obedient. With this overview of Part G, we now provide a brief synopsis of each chapter.

Chapter 67, Humanoids, provides a concise overview of the state of the art in creating human-like machines, starting with a historical and philosophical discussion on the human example and understanding intelligence. These machines are capable of bipedal locomotion and manipulation. In addition, humanoid robots can take advantage of their entire body (e.g., lifting objects while moving the body to compensate for the load). Control issues specific to humanoids include static and dynamic stability during a mobile manipulation action. Humanoid robots interact with humans via perception systems and should be capable of interpreting behavior and mood as well as via speech systems for interpreting human language.

Chapter 68, Human Motion Reconstruction, describes the most recent algorithms that rely on data from motion capture systems to synthesize human-like motion models for machines. The chapter introduces two models for information capture: optical motion capture and mechanical motion capture. The skeleton model is computed on the captured data using kinematics and dynamics models. Musculoskeletal models can also be computed for motion analysis involving muscles. The chapter discussed model identification techniques, segmentation of human motion, classification of human motion, as well as temporal sequencing and linguistic classification of human motion. The chapter concludes with a survey of techniques for motion reconstruction for robots.

Chapter 69, Physical Human-Robot Interaction, discusses what happens when humans and robots share the same workspace and come into contact with one another. Safety can be jeopardized by mechanical failures, operator errors, or software problems. Designing and controlling robots with safety guarantees is a very important precondition for physical human–robot interaction (pHRI). The chapter discusses safety standards for pHRI and surveys several approaches to safety.

Chapter 70, Human Robot Augmentation, introduces wearable robotics systems that enhance the capabilities of the humans wearing them, while allowing the humans to control them to enhance their performance in a task-specific way. There are three types of devices that deliver human augmentation:

- i) Prostheses, for the functional replacement of human limbs
- ii) Powered orthoses, which function is to actively operate in parallel with unhealthy human joints
- iii) Robotic exoskeletons that operate in parallel with healthy human limbs.

The chapter describes prostheses, powered orthoses and exoskeletons for upper limb, lower limbs and whole body structures. State-of-the-art devices together with their functionalities and main robotics components are presented for each class of wearable system. Critical design issues and open research aspects are reported.

Chapter 71, Cognitive Human Robot Interaction, considers human(s), robot(s), and their joint actions as a cognitive system. This chapter surveys the state of the art in modeling, algorithms, and design guidelines to enable the design of systems where humans and robots can interact. The chapter describes the representations and actions that allow robots to participate in joint activities with people and the models of joint activity for human-robot interaction. The chapter also describes recent research on developing a deeper understanding of human expectations and cognitive responses to robot actions. This chapter draws on research questions and advances from a wide range of fields including computer science, cognitive science, linguistics, and robotics.

Chapter 72, Social Robotics, discusses the creation of robots designed to interact with people in a social and emotional way for applications in education, entertainment, health care, etc. These robots' embodiment is life-like and they are capable of multi-modal communication. The chapter uses a case study of the Kismet robot to illustrate the idea of a machine capable of projecting emotion. The chapter surveys some basic approaches to giving robots sociocognitive skills such as shared attention, emotional empathy, and mental perspective tasking.

Chapter 73, Socially Assistive Robotics, covers the design of human-robot systems that use verbal and non-verbal expression and communication to interact and assist users through social rather than physical interaction. Socially assistive robotics (SAR) focuses on the challenges of providing motivation, coaching, training, and rehabilitation through non-physical interaction; such systems have been validated in hands-off stroke rehabilitation, social skill training of children with autism, and eldercare, among others. This chapter reviews the critical societal issues that have motivated research into socially assistive robotics, describes the reason why physical robots rather than virtual agents are essential to this, highlights the major research issues within this area, describes the primary application domains and populations where SAR research has shown an impact, and closes with some of the ethical and safety issues.

Chapter 74, Learning from Humans, covers important topics about how we approach teaching robots

what to do by providing either good or bad examples. This is an intuitive approach to robot control and learning of tasks with the potential of opening robot applications to non-expert users. The chapter starts by discussing what it means for a robot to learn a new skill and surveys several learning approaches for this. Biologically oriented learning approaches such as conceptual models of imitation learning and neural models of imitation learning are also introduced. The chapter concludes with several open issues in robot programming by demonstration.

Chapter 75, Biologically Inspired Robots, starts with a discussion of the difference between bio-inspired and biomimetic robots. Bio-inspired robots seek to reproduce a natural phenomenon but not necessarily the underlying means. Biomimetic robots reproduce both the natural phenomenon and the means. The chapter starts with a survey of bio-inspired morphologies. A survey of bio-inspired sensors from vision to audio, touch, smell, and taste is then presented. Bio-inspired actuators include locomotion topics such as crawling, legged locomotion, climbing swimming, flying, and manipulation. The chapter also examines bio-inspiration in the context of control and planning. This includes behavior-based architectures, learning robots, evolving robots, and developing robots. Finally, the chapter examines how to make machines self-sustaining from an energy point of view.

Chapter 76, Evolutionary Robotics, discusses a method for creating robots that is inspired by the Darwinian principle of selective reproduction of the fittest captured by evolutionary algorithms. The chapter introduces the evolutionary computation method and presents several case studies. Because the evolutionary method requires intensive computation, it is often run in simulation and the final result is transferred to the robot platform. However, in the recent past there were several successes with running evolutionary algorithms in real time on physical platforms to achieve complex behaviors such as learning to walk.

Chapter 77, Neurobotics: From Vision to Action, looks at how neuroethology, the study of brain mechanisms for animal behavior, inspires the creation of a central nervous system for a machine. The chapter presents several case studies that sample this bio-inspired design of robot controllers structurally and functionally: the optic flow in bees and robots, visually guided behaviors in frogs and robots, and navigation in rats and robots. The chapter then examines the role of the cerebellum in motion control and the role of mirror systems. The chapter concludes by observing the brain has evolved to serve as action-oriented percep-

tion, which is a useful guiding principle for building robot controllers.

Chapter 78, Perceptual Robotics, discusses principles derived from high-level cognitive processing in vision in the human brain that have led to results in robotics and computer vision. The chapter is focused on the technical realization of perceptual functions in robots by examining relationships between biological perception and robotics systems. Object recognition is used as an exemplary task and issues such as representation, structural description models, neural representations, as well as recognition and learning algorithms are discussed. Next, example-based movement representations are examined to establish the connection between the functionality of the visual cortex and a class of computer vision algorithms.

Chapter 79, Robotics for Education, provides an overview of the key ingredients that make successful education robots possible. It begins with a survey of robot tournaments, which are the most prevalent mechanism for educating young students in robotics. Robot tournaments have already impacted tens of thousands of students across diverse geographic and age group boundaries. Next, the chapter technology stan-

dards required for effective use of robots in education. Educational robot devices consist of both hardware (pre-assembled or as kits or components) and software (both as source code and programming environments). The chapter surveys the physical robot platforms that have achieved notable success, and the software that enabled the interaction with young students (that is, the low-level controllers that interface those platforms to high-level computation and the top-level programming environments.) Finally, the chapter describes how conventional analytical tools may be used to evaluate unconventional educational programs that use robots.

Chapter 80, Roboethics: Social and Ethical Implications, discusses the social and ethical implications in a society where robots coexist with humans. Starting with a philosophical introspection into the dangers of unlimited use of technology, the chapter argues for the need for a new ethics of robots. Many other factors, including the cultural differences in societies ready to accept robots, define this need. The chapter surveys the code of ethics, privacy, accuracy, intellectual property, and access, which could be adopted by robotics. A taxonomy of robot types, along with socio-ethical issues for each robot type is then presented.



67. Humanoids

Paul Fitzpatrick, Kensuke Harada, Charles C. Kemp, Yoshio Matsumoto, Kazuhito Yokoi, Eiichi Yoshida

Humanoid robots selectively immitate aspects of human form and behavior. Humanoids come in a variety of shapes and sizes, from complete human-size legged robots to isolated robotic heads with human-like sensing and expression. This chapter highlights significant humanoid platforms and achievements, and discusses some of the underlying goals behind this area of robotics. Humanoids tend to require the integration of many of the methods covered in detail within other chapters of this handbook, so this chapter focuses on distinctive aspects of humanoid robotics with liberal cross-referencing.

This chapter examines what motivates researchers to pursue humanoid robotics, and provides a taste of the evolution of this field over time. It summarizes work on legged humanoid locomotion, whole-body activities, and approaches to human-robot communication. It concludes with a brief discussion of factors that may influence the future of humanoid robots.

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67.1 Why Humanoids?

Throughout history, the human body and mind have inspired artists, engineers, and scientists. The field of humanoid robotics focuses on the creation of robots that are directly inspired by human capabilities (Chap. 75). These robots usually share similar kinematics to hu-

mans, as well as similar sensing and behavior. The motivations that have driven the development of humanoid robots vary widely. For example, people have developed humanoid robots to serve as general-purpose mechanical workers, entertainers, and test-beds for theories

from neuroscience and experimental psychology [67.1–3].

Notably, while this chapter focuses on robots that have been explicitly designated as humanoid robots by their creators, the lines between these robots and others can be blurry. Many robots share characteristics with humans, or have been inspired by humans.

67.1.1 The Human Example

On a daily basis, humans perform important tasks that are well beyond the capabilities of current robots. Moreover, humans are generalists with the ability to perform a wide variety of distinct tasks. Roboticians would like to create robots with comparable versatility and skill. Considering the physical and computational mechanisms that enable a person to perform a task is a common approach to automating it. Exactly what to borrow from the human example is controversial. The literal-minded approach of creating humanoid robots may not be the best way to achieve some human-like capabilities (Chap. 65). For example, dishwashing machines bear little similarity to the manual dishwashing they replace.

67.1.2 The Pleasing Mirror

Humans are humanity's favorite subject. A quick look at popular magazines, videos, and books should be enough to convince any alien observer that humanity is obsessed with itself. The nature of this obsession is not fully understood, but aspects of it have influenced the field of humanoid robotics.

Humans are social animals that generally like to observe and interact with one another [67.4]. Moreover, people are highly attuned to human characteristics, such as the sound of human voices and the appearance of human faces and body motion [67.5–7]. Infants show preferences for these types of stimuli at a young age, and adults appear to use specialized mental resources when interpreting these stimuli. By mimicking human characteristics, humanoid robots can engage these same preferences and mental resources.

Humanity's interest in itself has been reflected in media as diverse as cave paintings, sculpture, mechanical toys, photographs, and computer animation. Artists have consistently attempted to portray people with the latest tools at their disposal. Robotics serves as a powerful new medium that enables the creation of artifacts that operate within the real world and exhibit both human form and behavior [67.8].

Popular works of fiction have frequently included influential portrayals of humanoid robots and human-made humanoid creatures. For example, *Karel Čapek's* science fiction play *Rossum's Universal*

Robots (R.U.R.) from 1920 centers around the story of artificial people created in a factory [67.9]. Many other works have included explicit representations of humanoid robots, such as the robot Maria in *Fritz Lang's* 1927 film *Metropolis* [67.10], and the thoughtful portrayal of humanoid robotics by *Isaac Asimov* in works such as *The Caves of Steel* from 1954 [67.11]. The long history of humanoid robots in science fiction has influenced generations of researchers, as well as the general public, and serves as further evidence that people are drawn to the idea of humanoid robots.

67.1.3 Understanding Intelligence

Many researchers in the humanoid robotics community see humanoid robots as a tool with which to better understand humans [67.3, 12]. Humanoid robots offer an avenue to test understanding through construction (*synthesis*), and thereby complement the *analysis* provided by researchers in disciplines such as cognitive science.

Researchers have sought to better immitate human intelligence using humanoid robotics [67.13]. Developmental psychologists, linguists, and others have found strong links between the human body and human cognition [67.14]. By being embodied in a manner similar to humans, and situated within human environments, humanoid robots may be able to exploit similar mechanisms for artificial intelligence (AI). Researchers are also attempting to find methods that will enable robots to develop autonomously in a manner akin to human infants [67.15]. Some of these researchers use humanoid robots that can physically explore the world in a manner similar to humans [67.16].

67.1.4 Human Environments

People inhabit environments that accommodate human form and human behavior [67.17, 18]. Many important everyday objects fit in a person's hand and are light enough to be transported conveniently by a person. Human tools match human dexterity. Doors tend to be a convenient size for people to walk through. Tables and desks are at a height that is well matched to the human body and senses. Humanoid robots can potentially take advantage of these same accommodations, thereby simplifying tasks and avoiding the need to alter the environment for the robot [67.19]. For example, humanoid robots and people could potentially collaborate with one another in the same space using the same tools [67.20]. Humanoid robots can also interface with machinery that does not include drive-by-wire controls, as shown by the teleoperated robot in the cockpit of a backhoe in Fig. 67.1 [67.21].

Robots with legs and human-like behavior could potentially traverse the same environments that humans traverse, such as rugged outdoor environments and the industrial plant shown in Fig. 67.2, which has stairs and handrails designed for human use [67.22]. In addition to mobility advantages, legs have the potential to help in other ways. For example, legs could enable a humanoid robot to change its posture in order to lean into something, pull with the weight of its body, or crawl under an obstacle [67.23, 24].

The Fukushima Daiichi nuclear disaster, which occurred in March 2011 in Japan, is a compelling example scenario for robots. The disaster resulted in human environments that were unsafe for humans. Robots capable of performing diverse tasks in these environ-

ments via remote control would have been valuable. Future humanoid robots may be able to access similar environments using narrow passageways, ladders, and other environmental features designed for people (Fig. 67.3). Likewise, they may be able to remotely perform tasks involving control panels, valves, and tools designed for people. This type of scenario



Fig. 67.1 The humanoid robot HRP-1S (HRP: humanoid robot project) driving a backhoe (courtesy Kawasaki Heavy Industries, Tokyu Construction and National Institute of Advanced Industrial Science and Technology (Japan) (AIST)). The robot can be teleoperated by a human operator to control the backhoe remotely. The same robot could potentially interface with many different unmodified machines



Fig. 67.2 HRP-1 operating in a mockup of an industrial plant (courtesy Mitsubishi Heavy Industries)



Fig. 67.3 An image of supposed disaster-response scenario DARPA Robotics Challenge



Fig. 67.4 The humanoid robot HRP-2 dancing with a human (after [67.25]). The human is a master of a traditional Japanese dance whose dancing was recorded by a motion-capture system, and transformed for use by the robot

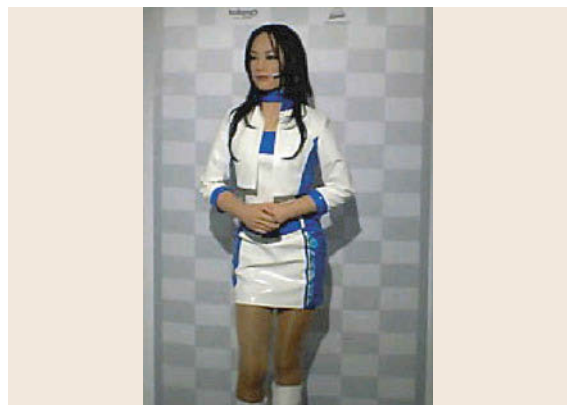


Fig. 67.5 Actroid (courtesy Kokoro), an android designed for entertainment, telepresence, and media roles

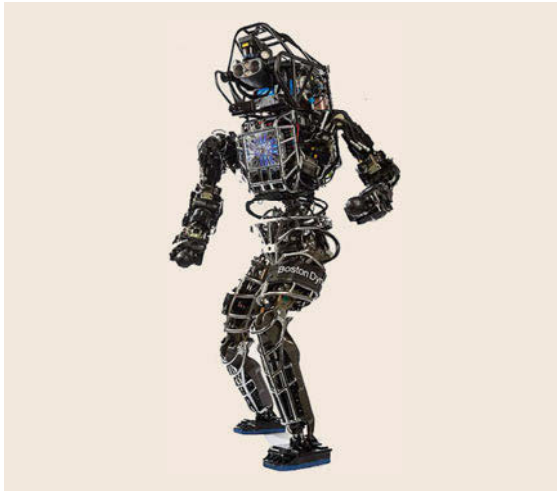


Fig. 67.6 Atlas robot provided as a platform for the DARPA Robotics Challenge (courtesy Boston Dynamics)

has inspired the DARPA (Defense Advanced Research Projects Agency) Robotics Challenge in which robots will compete by performing related tasks. Notably, DARPA plans for some teams to compete using Atlas humanoid robots from Boston Dynamics Fig. 67.6.

67.1.5 Human Interaction

People are accustomed to working with other people. Many types of communication rely on human form and behavior. Some types of natural gestures and expression involve subtle movements in the hands and face (Chap. 72). People can interpret eye gaze and facial expressions without training. Humanoid robots can potentially simplify and enhance human–robot interaction by taking advantage of the communication channels that already exist between people.

Similarly, people already have the ability to perform many desirable tasks. This task knowledge may be more readily transferred to humanoid robots than to a robot



Fig. 67.7 Petman is a humanoid robot that Boston Dynamics developed to test chemical protection clothing for the US military (after [67.26])

with a drastically different body. This is especially true of cultural actions centered around the human form (Fig. 67.4).

67.1.6 Entertainment, Culture, and Surrogates

Humanoid robots are inherently appropriate for some applications. For example, robots that resemble humans could play roles in entertainment, such as theater, theme parks, and companionship for adults (Fig. 67.5). Realism in form and function could make humanoid robots preferable to wax figures and animatronics.

A humanoid robot could serve as an avatar for telepresence, model clothing, test ergonomics, or serve other surrogate roles that fundamentally depend on the robot's similarity to a human. For example, Boston Dynamics developed the humanoid robot Petman to test clothing that is intended to protect military personnel from chemical agents (Fig. 67.7). Robotic prostheses and cosmeses also have a close relationship to humanoid robotics, since they seek to directly replace parts of the human body in function and form (Chap. 64).

67.2 History

There is a long history of mechanical systems with human form that perform human-like movements. For example, Al-Jazari designed a humanoid automaton in the 13th century [67.27], Leonardo da Vinci designed a humanoid automaton in the late 15th century [67.28], and in Japan there is a tradition of creating mechanical dolls called Karakuri ningyo that dates back to at least the 18th century [67.29]. In the 20th century, animatronics became an attraction

at theme parks. For example, in 1967 Disneyland opened its Pirate's of the Caribbean ride [67.30], which featured animatronic pirates that play back human-like movements synchronized with audio. Although programmable, these humanoid animatronic systems moved in a fixed open-loop fashion without sensing their environments.

In the second half of the 20th century, advances in digital computing enabled researchers to incorporate

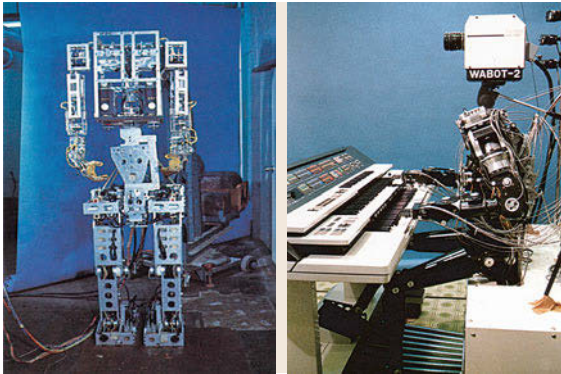


Fig. 67.8 (a) WABOT-1 (1973) and (b) WABOT-2 (1984; courtesy Humanoid Robotics Institute, Waseda University)

significant computation into their robots for sensing, intelligence, control, and actuation. Many roboticists developed isolated systems for sensing, locomotion, and manipulation that were inspired by human capabilities. However, the first humanoid robot to integrate all of these functions and capture widespread attention was Waseda robot (WABOT-1), developed by Ichiro Kato et al. at Waseda University in Japan in 1973 (Fig. 67.8).

The WABOT robots integrated functions that have been under constant elaboration since: visual object recognition, speech generation, speech recognition, bi-manual object manipulation, and bipedal walking. For instance, WABOT-2's ability to play a piano, publicized at the Tsukuba Science Expo in 1985, stimulated significant public interest.

In 1986, Honda began a confidential project to create a humanoid biped. Honda grew interested in humanoids, perhaps seeing in them devices of complexity comparable to cars with the potential to become high-volume consumer products one day. In 1996, Honda unveiled the Honda Humanoid P2, the result of this confidential project. P2 was the first full-scale humanoid capable of stable bipedal walking with onboard power and processing. Successive designs reduced its weight and improved its performance (Fig. 67.9). Compared to humanoids built by academic laboratories and small manufacturers, the Honda humanoids were a leap forward in sturdiness, using specially cast lightweight high-rigidity mechanical links, and harmonic drives with high torque capacity.

In parallel with these developments, the decade-long *Cog project* began in 1993 at the MIT Artificial Intelligence laboratory in the USA with the intention of



Fig. 67.9 (a) Honda P2 (180 cm tall, 210 kg), (b) P3 (160 cm, 130 kg), and (c) advanced step in innovative mobility (glossnoidx-ASIMO advanced step in innovative mobility) (120 cm, 43 kg) (after [67.31]; courtesy Honda)



Fig. 67.10 The humanoid robot Cog used neural oscillators in conjunction with compliant torque-controlled arms to perform a variety of everyday tasks with human tools, such as crank turning, hammering, sawing, and playing a snare drum (after [67.32]; courtesy Sam Ogden)

creating a humanoid robot that would, *learn to think by building on its bodily experiences to accomplish progressively more abstract tasks* [67.13]. This project gave rise to an upper-body humanoid robot whose design was heavily inspired by the biological and cognitive sciences (Fig. 67.10). Since the inception of the Cog project, researchers across the world have initiated many humanoid robotics projects and formed communities devoted to developmental robotics, autonomous mental development (AMD [67.33]), and epigenetic robotics [67.34].

As of the early 21st century, a large number of companies and academic researchers have become involved with humanoid robots and created new humanoid robots with distinctive characteristics.

67.3 What to Immitate?

Humanoid robots come in a variety of shapes and sizes that immitate different aspects of human form and behavior (Fig. 67.11). As discussed, the motivations that have driven the development of humanoid robots vary widely. These diverse motivations have led to a variety of humanoid robots that selectively emphasize some human characteristics, while deviating from others.

67.3.1 Body Parts

One of the most noticeable axes of variation in humanoid robots is the presence or absence of body parts. Some humanoid robots have focused solely on the head and face, others have a head with two arms mounted to a stationary torso, or a torso with wheels (for example, Fig. 67.12). Some humanoid robots even combine a highly-articulate face with arms, legs, and a torso.

67.3.2 Mechanics

Humanoid robots immitate various mechanical aspects of the human body, such as its kinematics, dynamics, geometry, material properties, and actuation. As such, humanoid robotics is closely related to the field of human biomechanics.

Humanoid robots often consist of rigid links with kinematics that approximate the kinematics of the human musculoskeletal system. Even a rigid-link model of human kinematics can have a very high number of degrees of freedom (DOF). A humanoid robot typically immitates degrees of freedom that are pertinent to its intended use. For example, humanoid robots rarely attempt to immitate the human shoulder's ability to translate or the flexibility of the human spine [67.35, 36]



Fig. 67.11 Kismet is an example of a humanoid head for social interaction

The human hand serves to further illustrate these issues. Modern humanoid robots frequently have two arms, each with seven degrees of freedom, but their hands vary considerably (Chap. 19). The human hand is highly complex with over 20 DOFs (i.e., approximately four DOFs per finger and a five-DOF thumb) in a very compact space with a compliant exterior, dense tactile sensing, and low distal mass. Researchers have approximated the human hand with varying levels of accuracy, including the anatomically correct testbed (ACT) hand, the 20-DOF Shadow Hand, the 12-DOF DLR-Hand-II (DLR: Deutsches Zentrum für Luft- und Raumfahrt), the 11-DOF Robonaut hand, and the 2-DOF Cog hand [67.37–41]. The ACT hand represents the high-fidelity end of the spectrum, since it approximates the bone structure, inertial properties, kinematics, and actuation of the human hand.

Actuation is another property of humanoid robots that varies considerably. Human actuation consists of a complex, highly-redundant system of variable-stiffness muscles. In contrast, many humanoid robots use a stiff, position-controlled actuator at each joint. There are early exceptions, such as the use of series elastic actuators in Cog's arms [67.32, 42], and various forms of compliant actuation have now become common in the arms of humanoid robots.

67.3.3 Sensors

Humanoid robots have made use of a variety of sensors including cameras, three-dimensional (3-D) cameras, laser rangefinders, microphone arrays, lavalier microphones, and pressure sensors. Some researchers choose to immitate human sensing by selecting sensors with



Fig. 67.12 The NASA (National Aeronautics and Space Administration) Robonaut consists of an upper body placed on a wheeled mobile base

clear human analogs and mounting these sensors on the humanoid robot in a manner that mimics the placement of human sensory organs. As discussed in Sect. 67.6, this is perhaps most evident in the use of cameras. Two to four cameras have often been mounted within the heads of humanoid robots with configurations similar to human eyes.

The justifications for this bias towards human-like sensing include the impact of sensing on natural human–robot interaction, the proven ability of the human senses to support human behavior, and aesthetics. For example, with respect to human–robot interaction, nonexperts can sometimes interpret the functioning and implications of a human-like sensor, such as a camera, more easily. Similarly, if a robot senses infrared or ultraviolet radiation, the robot can see a different world than the human. With respect to behavior, placement of sensors on the head of the robot allows the robot to sense the world from a vantage point that is similar to that of a human, which can be valu-

able for finding objects that are sitting on a desk or table.

Prominent humanoid robots have added additional sensors without human analogs. For example, Kismet used a camera mounted in its forehead to augment the two cameras in its servoed eyes, which simplified common tasks such as tracking faces. Similarly, versions of [ASIMO](#) have used a camera mounted on its lower torso that looks down at the floor in order to simplify obstacle detection and navigation during locomotion.

67.3.4 Other Characteristics

Other common forms of variation include the size of the robot, the extent to which the robot attempts to appear like a human, and the activities the robot performs. The remainder of this chapter provides examples from three active areas of humanoid robotics research: locomotion, whole-body activities, and morphological communication.

67.4 Locomotion

Bipedal walking is a key research topic in humanoid robotics (see also Chap. 48, *Legged Robots*, for a review of this topic in the context of locomotion in general). Legged locomotion is a challenging area of robotics research, and bipedal humanoid locomotion is especially challenging. Some small humanoid robots are able to achieve statically stable gaits by having large feet and a low center of mass, but large humanoids with a human-like weight distribution and body dimensions typically need to balance dynamically when walking bipedally.

67.4.1 Bipedal Locomotion

Currently the dominant methods for bipedal legged locomotion with humanoids make use of the zero-moment point ([ZMP](#)) criterion to ensure that the robot does not fall over [67.43]. As discussed in detail in Chap. 48, control of the robot's body such that the [ZMP](#) sits within the support polygon of the robot's foot ensures that the foot remains planted on the ground, assuming that friction is high enough to avoid slipping. The [ZMP](#) can be used to plan walking patterns that make the robot dynamically stable while walking. Conventionally, biped locomotion had been offline generated by solving an ordinally differential equation with respect to the motion of the [COG](#) (center of gravity) given a desired trajectory of the [ZMP](#).

Recently, several extensions have been done for the [ZMP](#) based biped gait generation as shown in the following:

Realtime Walking Pattern Generation

By solving the ordinally differential equation in realtime, biped gait is generated in realtime [67.44, 45]. Since the realtime walking pattern generator enables us to change the landing positions of foot in realtime, it is used in various situations; in [67.46], the landing position of the foot changes in accordance with the hand reaction force as will be described more concretely in the subsection of *manipulation*. As shown in Fig. 67.13 [67.47], the walking pattern is generated in realtime in accordance with the amount of external disturbance applied to the robot. In this case, after the torso of a robot is pushed by a human, biped gait for a few steps is generated in realtime to recover the balance. In [67.48], the humanoid robot [ASIMO](#) walks in the environment with moving obstacles. By using the estimation of the object motion, the walking pattern of the robot is generated in realtime. Fig. 67.14 [67.49] shows the biped locomotion on uneven terrain. In this experiment, the shape of the environment is measured by a laser range sensor. According to the shape information of the environment, the landing position on uneven terrain is calculated in realtime.



Fig. 67.13 Experiment of push recovery

Running
By additionally considering the flight phase to the ZMP based walking pattern generator, running motion of biped robot is generate [67.50–52]. Fig. 67.15 [67.52] shows an example of running motion by a biped humanoid robot. Running motion



Fig. 67.14 Experiment on biped gait on uneven terrain

of a human-sized humanoid robot with 7 km/h is realized.

Extension of ZMP Based Method
Although the ZMP is a two dimensional information defined for the interaction between a robot and the ground surface, a robot applies 6 dimensional force/moment onto the ground. Hence, just by regulating the position of the ZMP, it is impossible to control all dimension of the interaction force/moment. More concretely speaking, the robot may slip on the ground surface or may loose contact with the ground. Research on biped locomotion considering full 6 dimensional force/moment has been don [67.53, 54].

Human-Like Walking Motion
The biped locomotion generated just by using the ZMP may not be a human-like one. Challenge has been done to generate a human-like biped gait of a humanoid robo [67.55]. Fig. 67.16 [67.55] showws a biped locomotion where single toe support, knee stretching and human like swing leg trajectory are applied. It is compared with the human walking motion where the model belongs to *Walking Studio Rei*.

Force/Moment Controller
Bipedal walking needs to be robust to unexpected disturbances encountered during the execution of planned

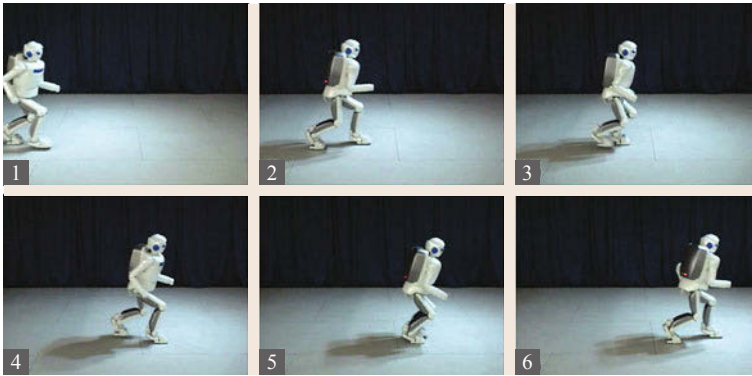


Fig. 67.15 Example of running motion

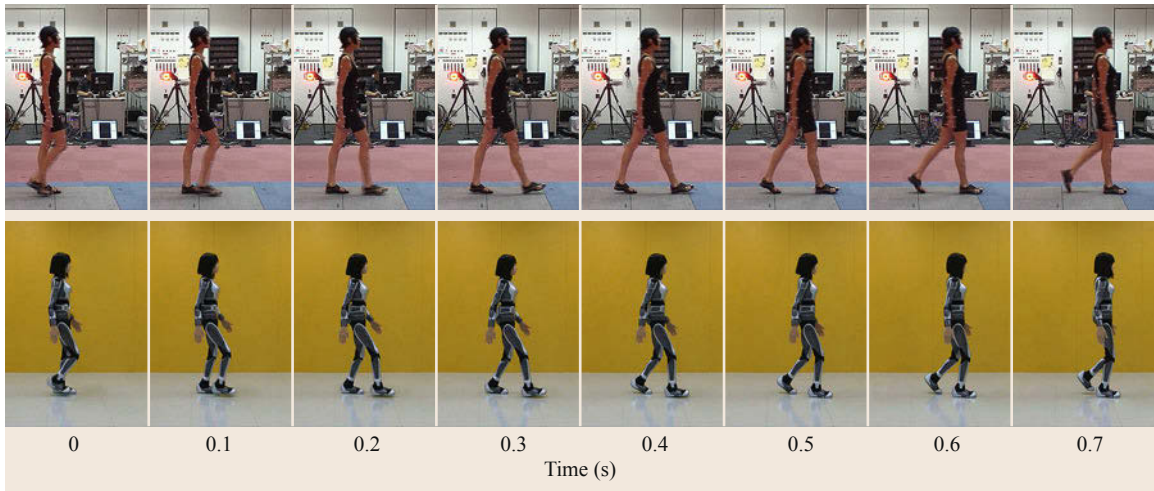


Fig. 67.16 Human like walking motion compared with human motion

walking patterns. In these situations, walking can sometimes be stabilized with feedback control and appropriate sensin [67.56]. Many humanoid robots, such as Honda's [ASIMO](#), make use of accelerometers, gyroscopes, and six-axis force/torque sensors to provide feedback to the robot during locomotion.

Force/torque sensors have long been applied to manipulators for the implementation of force control, but force/torque sensors with sufficient robustness to handle foot impact for a full-size humanoid robot are relatively new. When the foot of the robot touches down, the foot receives an impact which can disturb its walking. This impact can be rather large, especially when the robot is walking quickly. Some feet now incorporate a spring and damper mechanism as shown in [Fig. 67.17](#) in order to mitigate these problems.

Passive-Gait-Based Approach

Alternative to the [ZMP](#)-based approach, researchers have begun to use the principles of bipedal passive-dynamic walkers to develop powered bipedal walkers

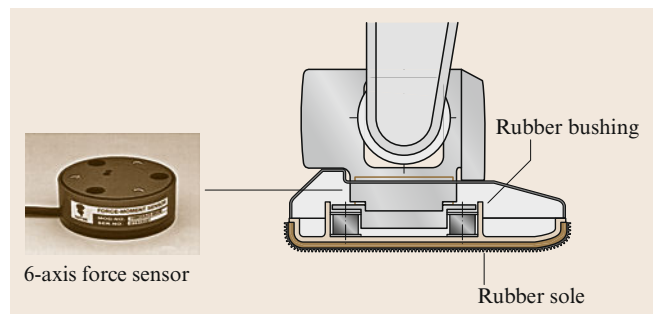


Fig. 67.17 Example of a humanoid foot structure for legged locomotion that uses compliance and force/torque sensing

that walk with high efficiency in a human-like way by exploiting natural dynamics ([Fig. 67.18](#) [67.57]).

67.4.2 Other Various Locomotion Styles

Most humanoid robots have two legs and two arms. Here, in addition to the legs, the arms can be used to

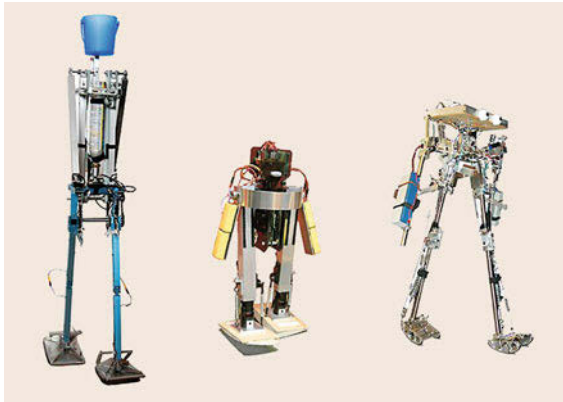


Fig. 67.18 These robots from Delft, MIT and Cornell (left to right) are designed to exploit their natural dynamics when walking (after [67.57]; courtesy Steven H. Collins)

enhance the mobility of a humanoid robot. For example, when a robot walks while grasping a handrail, the contact could potentially increase the stability of the robot. Attempt [67.58] have been done to generate the motion of a humanoid robot by using the arms in addition to the legs to enhance its mobility of it. As shown in Fig. 67.19 [67.58], a humanoid robot walking on uneven terrain sometimes uses to increase the robot's stability.

A human-scale robot should expect to fall from time to time in realistic conditions. A humanoid robot may fall down due to a large disturbance even if the motion is planned carefully and a sophisticated feedback controller is applied to the robot. In this event, the robot could be damaged significantly during a fall, and could

also damage the environment or injure people who are nearby. An important area of research is how to control the robot's fall in order to gracefully recover or minimize damage. The Sony **QRIO** (Quest for cuRIOsity) can control its falling motions in order to reduce the impact of touch down [67.50], although it is of a relatively small size (which simplifies the problem). *Fujiwara* et al. developed a falling motion controller for a human-size humanoid robot that is falling backwards [67.59]. Figure 67.20 shows an example of a controlled falling motion. The general problem is still very much an active area of research. Similarly, there is also the issue of getting back up again [67.60] (Fig. 67.21).

67.4.3 Localization and Navigation Among Obstacles

In order for a humanoid robot to walk in unmodeled environments, localization and obstacle detection are essential. Wheeled robots encounter similar issues while navigating, but full bipedal humanoids have more-specialized requirements. For example, bipedal humanoids have the ability to control contact with the world through their highly articulate legs.

Artificial landmarks can simplify localization. As shown in Fig. 67.22, Honda's **ASIMO** uses a camera mounted on its lower torso that looks down at the floor to find artificial markers for position correction [67.61]. Accurate positioning is important for long-distance navigation and stair climbing, since slippage usually occurs while walking and accumulated positional and directional errors can lead to severe failures.

Obstacle avoidance is also an important function for locomotion. Disparity images generated by stereo vi-

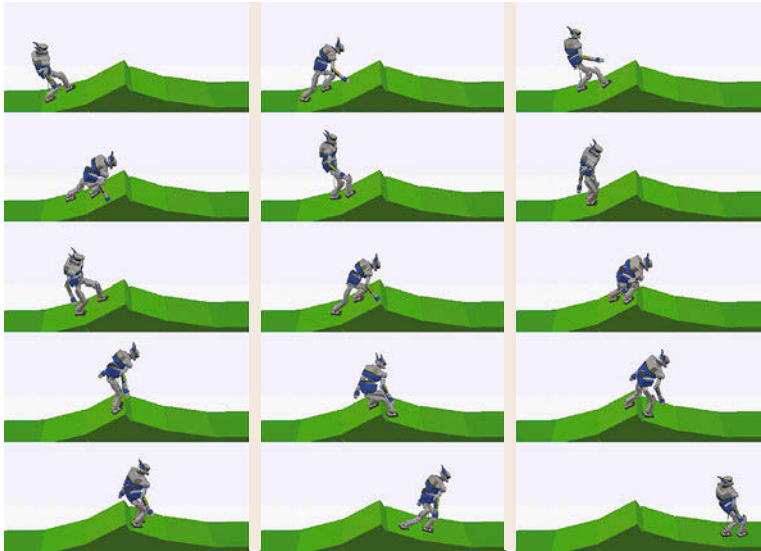


Fig. 67.19 Humanoid robot walking on uneven terrain by utilizing hand contact



Fig. 67.20 Example of controlled falling-down motion

Fig. 67.21 The humanoid robot **HRP-2P** getting up from a lying-down position ►

sion have been utilized for this purpose. For example, the plane segment finder [67.62] developed by *Okada et al.* helps detect traversable areas. Figure 67.23 shows the result of detecting clear areas of the floor plane appropriate for gait generation.

Humanoids require a great deal of computation due to the need for sophisticated sensing and control. Customized computational hardware may help mitigate this problem. For example, Sony's humanoid robot **QRIO** is equipped with a field-programmable gate array (**FPGA**) to generate disparity maps in real time from the stereo cameras. This real-time vision system has been used to detect floor areas, stair steps, and obstacles for navigation [67.63, 64].

67.4.4 Generating Motions when in Contact with an Object

Many approaches to whole-body motion generation assume that the robot is only in contact with the ground. When a humanoid robot's hands make contact with the environment, it can no longer maintain balance using the conventional **ZMP** property defined by the center of pressure of the supporting feet [67.65]. This leads to significant challenges for whole-body activities, especially since the properties of the environment with which the robot is making contact may not be known in advance.

Harada et al. have introduced generalized **ZMP** (**GZMP**) as a method of handling some of these issues, such as the hand reaction forces generated from contact with the environment [67.66]. Researchers have developed methods that directly make use of the six-dimensional force/torque acting on the robot at the hands, which can be sensed with conventional force/torque sensors placed at the wrists [67.67]. Researchers have also developed specialized methods for generating stable robot motion while an object is being manipulated [67.46, 65, 68–70].

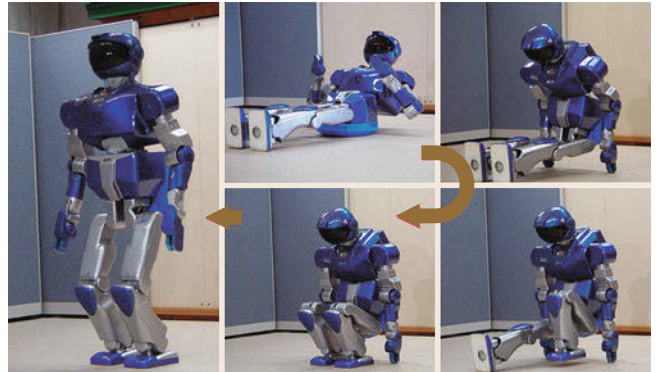
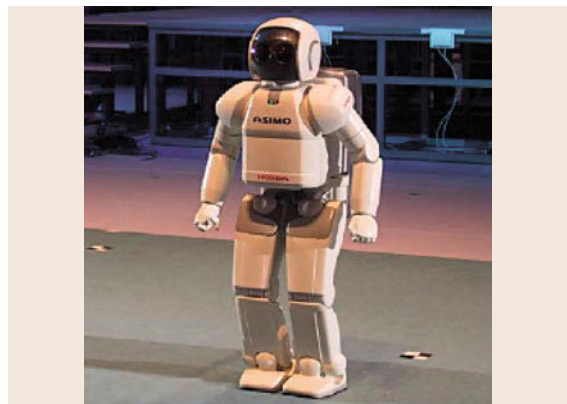


Fig. 67.22 **ASIMO** and artificial landmarks on the floor

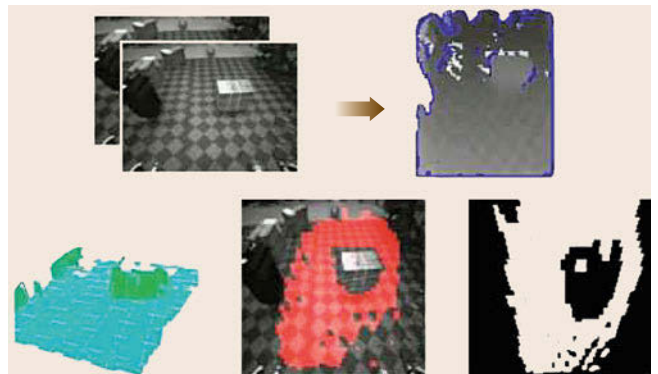


Fig. 67.23 Plane segment finder for detecting traversable floor area

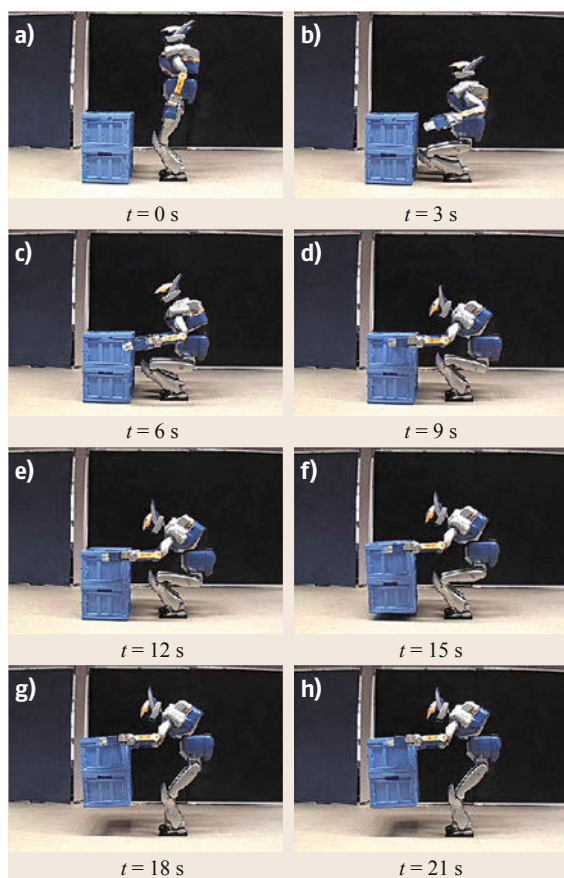


Fig. 67.24 (a–h) Lifting an object while moving the waist to compensate for the load (after [67.71])

Carrying an Object

In a manner analogous to the previously described methods, coarse motions that do not consider the hand reaction forces can be modified [67.65, 68, 71, 72]. Figure 67.24 shows an experimental result of carrying an object that weighs 8 kg [67.71]. Based on measurements of the hand reaction force, the position of the waist is modified to compensate for the load and maintain stability.

Pushing an Object

As another example of using force sensing to adapt behavior, consider the problem of pushing a large object placed on the floor. For such a task, if the gait

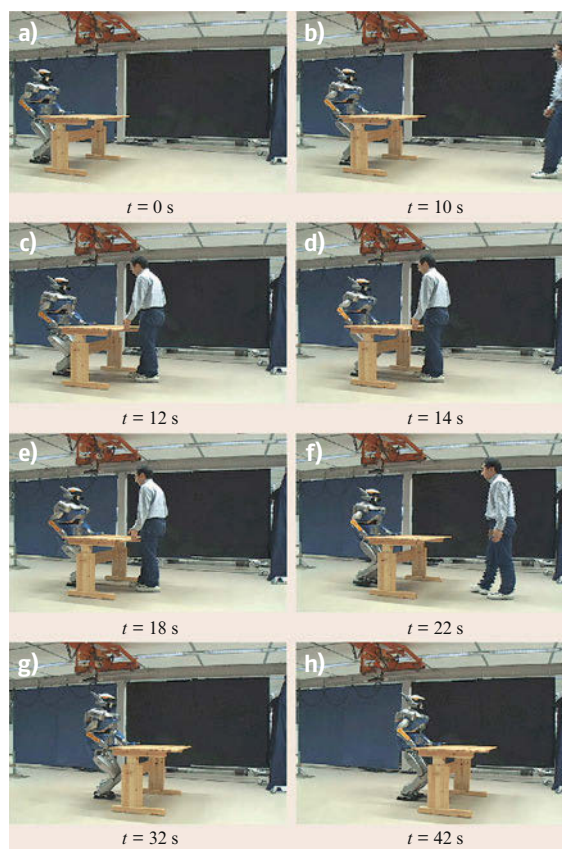


Fig. 67.25 (a–h) Example of pushing manipulation and cooperation (after [67.46])

pattern is determined before the robot actually moves, the robot may not stay balanced if the weight of the object or the friction coefficient between the object and the floor is different from the predicted values. To address this problem, the gait pattern can be adaptively changed depending on the output of a force sensor at the end of the arms in order to handle changes in the object's weight and the friction coefficient [67.46].

Figure 67.25 shows an experimental result for this approach [67.46]. In the experiment, the table weighs about 10 kg. Even though the motion of the table is disturbed externally during the experiment, the robot stays balanced by adaptively changing its gait pattern based on the measured forces.

67.5 Whole-Body Activities

The two previous sections have focused on humanoid locomotion and manipulation separately. This section outlines whole-body motions that require coordinated control of arms and legs to perform various tasks, such as carrying a bulky objects, climbing a ladder, or going through narrow spaces with contact supports on the environment. Humanoid motion is characterized by their redundancy and underactuation (Chaps. 10 and 17). Unlike fixed industrial robots, it has a floating base (usually it is set at the pelvis) that can only be controlled through the leg locomotion or multiple contact motion involving arms and legs. It is therefore essential how to define the desired task and to generate the motion that achieves it. Since humanoids have a redundant structure, a general approach is first to generate coarse motion, and then to transform it into a whole-body coordinated joint trajectory that is executed by a controller maintaining the stability through sensor feedback, as illustrated in Fig. 67.26. The first half of this section addresses the first two components of this general approach.

The latter half of this section deals with issues related to various complex whole-body motion that the basic conversion methods addressed in Sect. 67.5.2 could not always resolve. Resolution of various concurrent tasks, including those expressed as inequality and dynamic constraints is presented in Sect. 67.5.3. This framework can be applied to a reaching task while keeping the visibility of the object, as well as footstep planning. Finally, motion generation including multiple contacts is introduced as an advanced topic in Sect. 67.5.4. A wide variety of its application is expected to extend the activity fields of humanoids in cluttered environments where the humanoid should maintain its balance by supporting its body on non-coplanar contact points.

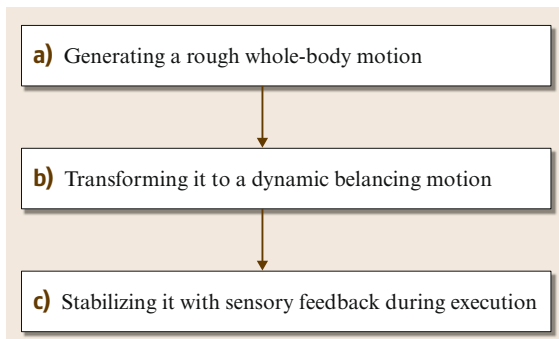


Fig. 67.26 Overview of motion-generation stages for a balancing robot

67.5.1 Coarse Whole-Body Motion

There are several ways to generate coarse humanoid motion:

1. Using motion capture system
2. Using graphical user interface (GUI)
3. Using automated motion planning
4. Using abstract task specification.

Using Motion Capture System

As humanoid robot has a human-like structure, a natural and common way of motion generation is using measured human motion. Motion retargeting from recorded human motion to digital characters is a well-studied area in computer animation. Typically a human subject performs actions while wearing easily detected markers on his or her body. The motion of these markers is recorded by cameras placed in the room, and software then infers the 3-D positions of these markers over time. A number of studies have been reported to convert the capture motions to humanoid whole-body motions through learning [67.73] and optimization [67.74, 75]. Figure 67.27 shows an example: the captured motions of a woman performing a Japanese traditional dance [67.76] that the performance in Fig. 67.4 is based on. Kinematic similarity allows using the captured motion as a reference for a humanoid's whole-body motion, by computing the corresponding joint angles from forming virtual links with several markers. However, due to dynamic differences, such as mass distributions and torque generation, captured motions are generally not stable nor feasible when applied to a humanoid. It is therefore necessary to adapt them to humanoid body as explained in Sect. 67.5.2.

Using GUI

Tools such as those used in character animation for computer graphics can also be used to design movements for humanoid robots. If the designer were forced to control each of the many degrees of freedom independently or to takes care of the balance, the process would be tedious and inefficient. One solution that enables non robotics expert to design robot motion is key-pose based approach on GUI, which allows the designer to define the *key-poses* of the desired motion with the help of inverse kinematics of the end effectors. The interface take care of the interpolation and dynamic balance compensation so that the input motion is feasible for the humanoid as explained later in Sect. 67.5.2. Figure 67.28 illustrates the overview of a GUI interface developed as *Choreonoid* for this purpose [67.77, 78].

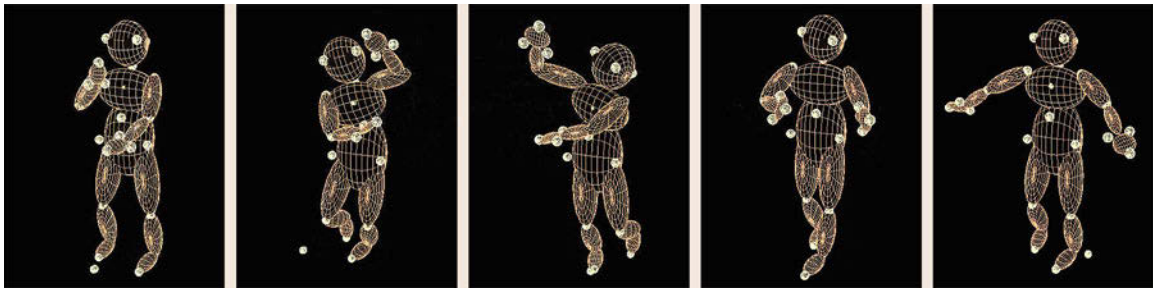


Fig. 67.27 A sequence of captured motion of dancing (after [67.76])

Using Automated Motion Planning
The previous two methods are based on mainly joint angles from a motion capture system or a GUI. If the purpose of the robot motion is going from one configuration to another without collisions and how the humanoid moves does not really matter, automated motion planning can provide efficient solutions (Chaps. 36 and 47).

Fast path-planning techniques such as rapidly-exploring random trees (RRT) can compute basic collision-free postures with static balance [67.79, 80] or walking paths [67.81] automatically with a simplified model. Figure 67.29 illustrates a humanoid carrying an object whose lower body is modeled by a bounding box. Given geometric models of the humanoid and the environment, initial and goal configurations, the planning system automatically searches for a path free of collisions at both upper and lower bodies. This coarse path can be converted into dynamically stable whole-body motion a walking pattern generator including upper-body motion compensation as described in Sect. 67.5.2. For further reading on humanoid motion planning, the

readers are referred to a book dedicated to this subject [67.82].

Using Abstract Task Specifications
Tasks for a humanoid to execute are not always specified in the joint space, but often in the workspace. For instance, if the humanoid wants to grasp an object on the table or floor, this task is expressed as the hand position and orientation in Cartesian space [67.83–87]. Another example is teleoperation: it is easier for the operator to guide an operational point, such as the end-effector or the head of the humanoid, rather than to give a whole-body joint configuration [67.88]. These tasks are represented in an abstract way by a smaller number of DOF than the redundant structure of humanoid. Figure 67.30 shows a motion of bimanual manipulation based on abstract representation of motion as a sequence of attractor points acting in the task space [67.89].

On the other hand, other constraints such as balancing or joint limits should also be taken into account to generate a whole-body motion to achieve the task.

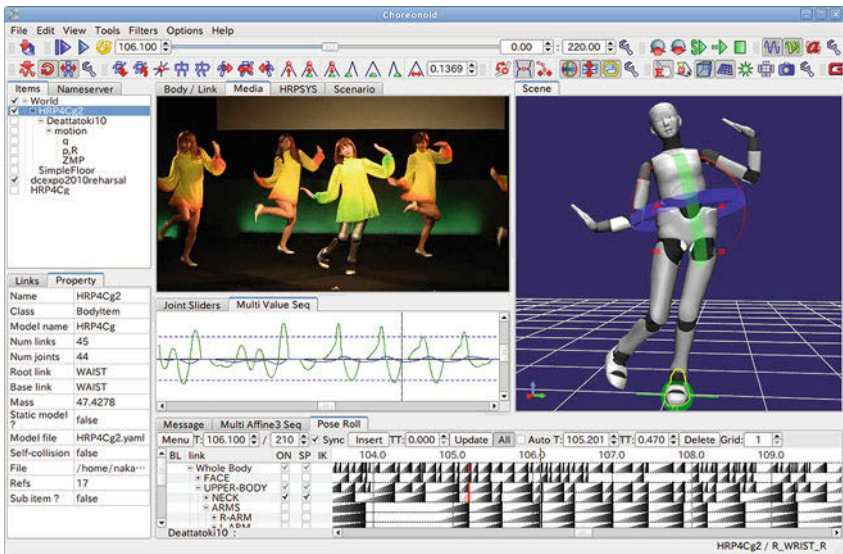


Fig. 67.28 A motion choreography tool working within the Choreonoid framework. In this tool, whole body motions of biped humanoid robots can be created with key-frame editing similar to computer graphics (CG) character animations (after [67.78])

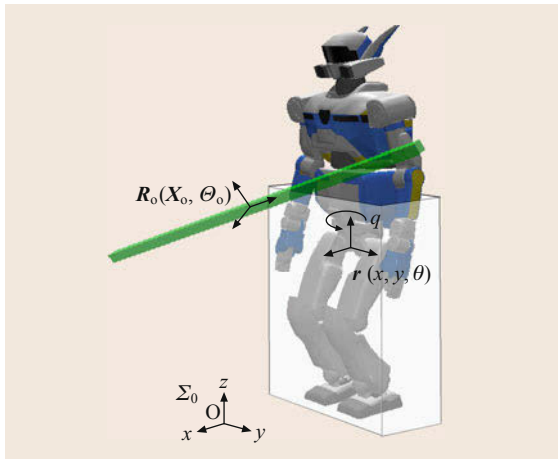


Fig. 67.29 Humanoid modeled by rectangle box with a bar. In the first stage the geometric and kinematic path planner generates collision-free path for the 9-DOF system including robot waist on the plane (3-DOF) and object (6-DOF)

A mechanism is therefore necessary that derives a humanoid positioning as well as a whole-body target posture from the abstract goal specification. Whereas the previously introduced GUI including automatic balancing is useful for cases with large free space, cluttered environments require integration of search techniques to compute a valid whole-body posture from the task [67.90,91]. Motion generation for multiple tasks and constraints is later discussed in Sect. 67.5.3.

67.5.2 Generating Dynamically Stable Motions

The methods presented in Sect. 67.5.1 can be useful when generating coarse motions for a humanoid robot, such as dance performance, manipulating or walking. However, for some of these methods the motions generated will not take into account the dynamic stability of the robot, and may result in the robot falling over. This subsection presents some approaches for con-

verting coarse motions to dynamically-stable motions, dynamic balancing algorithms and task-balance functional decomposition. In the former approach, all the joints including upper body are involved for whole-body balancing based on the reference motion, like kicking motion that needs upper body motion compensation. The latter uses mainly lower body for balancing or walking while upper body takes care of the desired tasks such as manipulation.

Dynamic Balancing

A framework called autobalancer is one of the pioneering studies for the dynamic whole-body balancing for humanoids. It all joint angles at every sample in time by solving a quadratic programming (QP) optimization problem in order to convert a given motion to a balanced one [67.92]. This method can be effective for a motion in which static balancing is dominant, such as when the humanoid is standing. The autobalancer calculates a whole-body motion first by fixing the center of gravity (COG) on the vertical axis which passes through a point in the support polygon of the humanoid. Then it keeps inertia moments around the COG at acceptable values in order to satisfy the balancing conditions. This technique was combined with a fast sampling-based motion planner to derive a dynamically motion by exploring configurations with balance constraints [67.79].

Resolved momentum control (RMC) [67.93] is a framework for whole-body control based on the linear and angular momentum of the entire robot. The robot is regarded as a single rigid body whose linear and angular momentum is to be controlled. At each point in time, this framework uses least squares to find joint velocities that will achieve the desired linear and angular momentum of the robot. Elements of the momentum can also be left unspecified as free variables, which is often done in practice with elements of the angular momentum. In addition to elements of the momentum, resolved momentum control requires that desired velocities for the feet be specified. This method has been applied to teleoperation [67.88] or stable reaching or kicking motions [67.93]. Other methods like dynamics

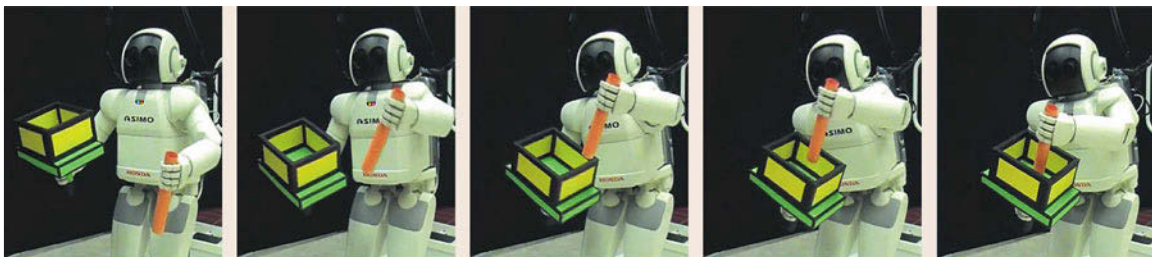


Fig. 67.30 Bimanual manipulation by humanoid robot ASIMO based on a motion representation using attractor dynamics in task space (after [67.89])

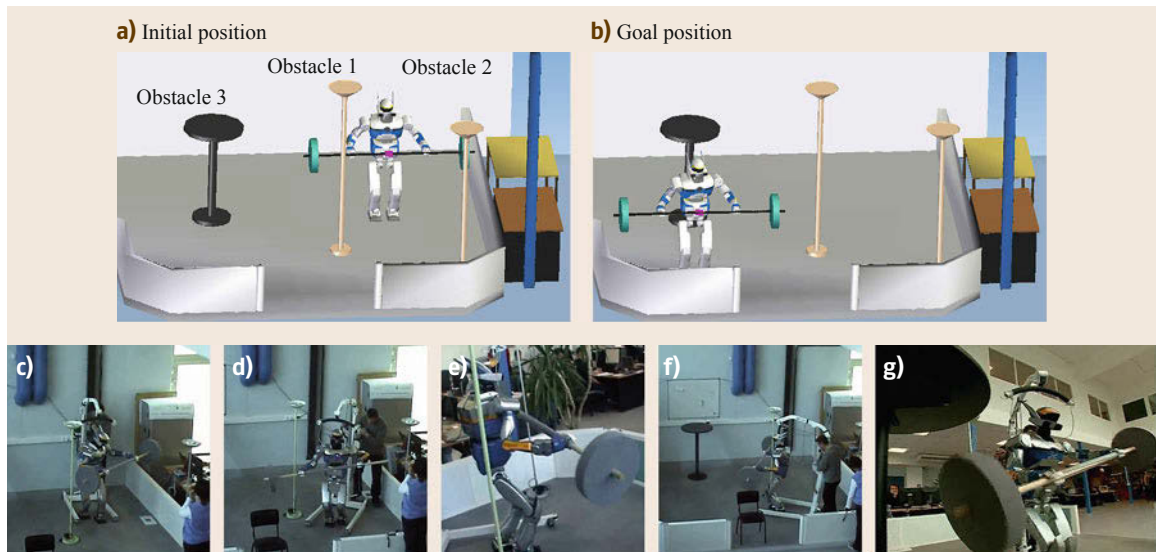


Fig. 67.31a–g A 3-D collision-free motion for bar-carrying task by humanoid robot HRP-2 from starting (a) an initial position to final configuration (goal position) (b) using whole-body motion (after [67.81]). The robot rotates the bar horizontally to make the bar go through a gap between poles whose distance is shorter than the of the bar (c–e). By making use of the concave part of the carried object (f) for 3-D collision avoidance, it arrives at the goal configuration with another avoidance motion (g) (VIDEO 594, VIDEO 598)

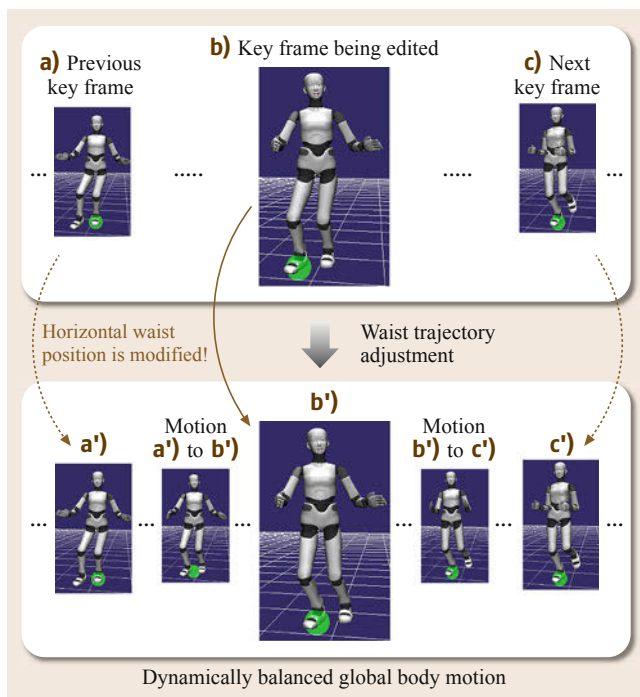


Fig. 67.32 Waist trajectory adjustment, which is automatically processed immediately after every time key poses are modified. As a result, horizontal waist positions of key poses are slightly modified and a dynamically balanced motion is obtained (after [67.77])

filter that makes reference motions dynamically feasible by a humanoid [67.94], upper-body motion compensation for Waseda bipedal humanoid (WABIAN) [67.95] have also been proposed as this type of approach.

Task-Balance Functional Decomposition

In this approach, dynamic stability is maintained during whole-body motion based on pattern generation or a balance compensation by the legs to maintain the ZMP inside the foot support area, while upper body is in charge of specified tasks such motions as manipulation or designed movement.

An iterative two-stage motion planning method has been proposed for a humanoid to perform manipulation and locomotion at the same time [67.81]. At the first stage, the motion planner generates the upper-body motion with a walking path of the bounding box of the lower body as in Fig. 67.29. The second stage overlays the desired upper-body motion on the dynamically stable walking motions generated by a dynamic walking pattern generator based on preview control of ZMP for a linear inverted pendulum model [67.96] (Chap. 48 and Sect. 67.4). This upper-body motion during walking induces errors in resulting ZMP from the reference, which may make the humanoid instable. By applying the preview control again to this ZMP error the necessary compensation motion can be computed as a horizontal offset on the waist position. If the resulting

whole-body motion is not collision-free, the planning process goes back to the first stage to reshape and this procedure is repeated until a valid motion is obtained. Figure 67.31, VIDEO 594 and VIDEO 598 show the resulting collision-free manipulation motion of a bar-shaped object in an environment populated with obstacles.

Lower-body motion compensation for dynamic balance is also used for GUI-based motion designing [67.77]. The GUI accepts a sequence of key-poses for the desired motion as the input and interpolates between them to compute the whole-body motion of the humanoid. Since the generated motion is not dynamically stable in general, both the key poses and the interpolated motion are adjusted to be dynamically balanced by applying the waist trajectory adjustment in such a way that the trajectory of the ZMP from body motion is always inside the foot support area. The adjustment only modifies the horizontal waist position of the key poses and the interpolated ones, for the adjusted motion to be as close as the original one (Fig. 67.32). The adjustment is automatically and immediately done every time a user has finished an edit operation so that the user can see the resulting motion.

67.5.3 Generating Whole-Body Motions with Various Tasks

The main purpose of the methods in previous section was to make the given coarse motion dynamically stable. One can think of a case the task is only given in an abstract manner, for instance reaching the end-effector in specified position and orientation in workspace, or aligning a camera axis in a direction. This section takes a step forward in order to generate automatically the motion to achieve the specified tasks by taking into account such constraints as balance, foot positions or joint limits at the same time. Generalized inverse kinematics technique with task priority and its extension is utilized as a key tool for local whole-body motion generation (Chap. 10).

The main particularities of humanoid robot from the viewpoint of inverse kinematics are the following: necessity of dynamic balancing, changing fixed root joint and floating base frame. Those issues should be dealt with appropriately depending on the task of the robot. Some extensions for more complex tasks including inequality constraints, footstep planning and dynamics are also mentioned at the last part of this section.

Dynamic Balancing and Walking

Some examples are shown the whole-body motion generation based on task priority generalized inverse kinematics. As shown in Chap. 10, this framework ac-

complishes first the task with the highest priority and then tries to achieve those with lower priority at the best in the null space of the higher-priority tasks.

Tasks are specified locally as a velocity in workspace, such as hand velocity to reach the target. The balance constraint can therefore be expressed as the velocity of the center of mass (COM). The ZMP-based pattern generator has the advantage that it outputs the velocity of the COM of dynamically stable walking motion from the reference ZMP trajectory, which can be easily integrated into this inverse kinematics framework by using COM Jacobian [67.97]. Figure 67.33 shows the whole-body reaching motion including a step to take a ball localized by a vision system [67.85]. The high priority is assigned to COM and foot motion to avoid falling in this example. As can be seen, the legs are used not only for stepping but also bending to reach a lower position in a manner coordinated with the upper body. The left arm moves backwards as the result of balancing task. Whole-body motions for manipulation of daily-life tools [67.84] or object pushing/lifting [67.98–100], and also for self-collision avoidance [67.101] have been implemented also based on a similar framework.

Another example is given in Fig. 67.34, VIDEO 595 and VIDEO 599 where the humanoid

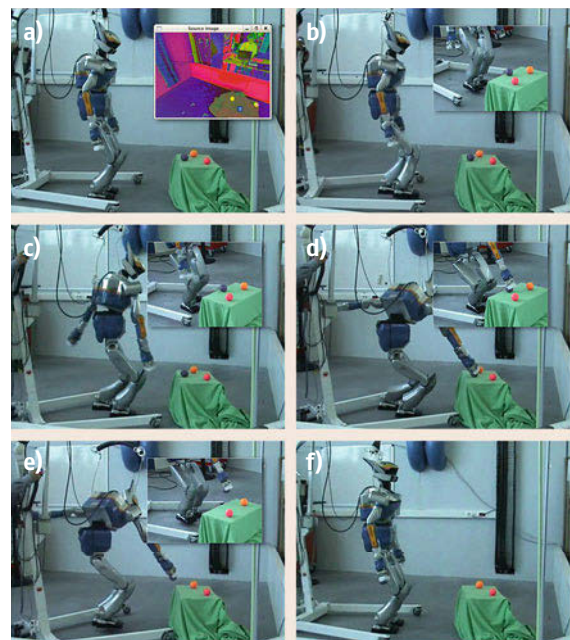


Fig. 67.33 (a–f) A whole-body grasping motion generated through task-priority generalized inverse kinematics (after [67.85]). Upper and lower bodies coordinate to achieve the desired grasping task while making a step and maintaining the balance

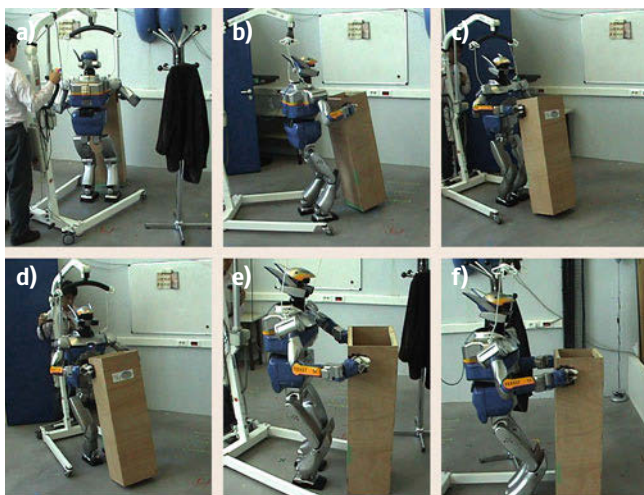


Fig. 67.34a–f Experiments of whole-body *pivoting* manipulation. Starting from the initial position (a) with obstacle at right-hand side, the humanoid robot manipulates the object backwards away from the wall (b). After switching motion direction to forward (c), the robot continues to manipulate the object to the goal position by avoiding the obstacle (the hanger) (d–f) (👁 VIDEO 595, 👁 VIDEO 599)

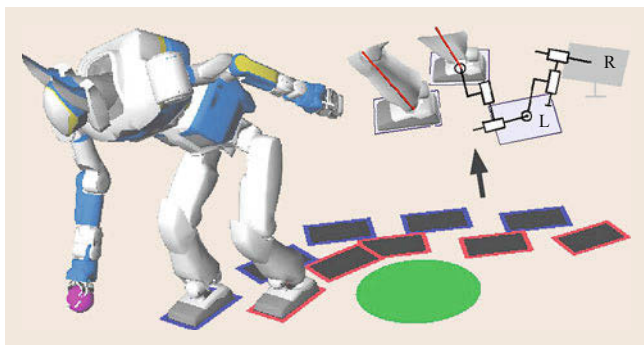


Fig. 67.35 Footstep planning modeled as a whole-body inverse kinematic problem (after [67.102]) (👁 VIDEO 596, 👁 VIDEO 600)

execute *pivoting* manipulation to carry a bulky object without lifting [67.86]. In this case, a coarse path of the object towards its goal position is first planned to compute the trajectory of the hands that perform the manipulation. Then foot positions are determined along the object path, from which the COM trajectory is derived using the dynamic walking pattern generator. Those tasks are provided to the inverse kinematics to generate the coordinated arm and leg motion for this complex manipulation. In addition to the dynamic balance, the change of the root joint is also considered to compute the whole-body motion when the support leg changes during walking. The same framework has been applied to a motion for catching a moving object

during walking where the task of visual tracking by the end-effector is integrated with dynamic walking motion [67.103].

Floating base frame of a humanoid sometimes brings difficulties in determining the whole-body configuration from a specific abstract task specified in workspace. In the methods mentioned above, the goal configuration is derived as a result of repeated computation of local generalized inverse kinematics. However, there are often cases where goal whole-body configurations is first needed to be used popular motion planning techniques searching in configuration space such as sampling-based planning. Some methods that derive the goal configuration based on inverse kinematics can be useful for this purpose [67.90, 91, 104] or a precomputed reachability map that characterizes the capacity of reaching in discretized workspace around the robot [67.105, 106].

Extensions for Complex Tasks

The whole-body motion generation with tasks can be extended to cope with more complex tasks such as stepping and those expressed as inequality or dynamic constraints.

One extension particular to humanoid is incorporating stepping in the framework of whole-body generalized inverse kinematics. Kanoun et al. [67.102] introduced an augmented robot structure by introducing *virtual* planar links attached to a foot that represents footsteps as illustrated in Fig. 67.35, 👁 VIDEO 596 and 👁 VIDEO 600. This modeling makes it possible to solve the footstep planning as a problem of inverse kinematics, and also to determine the final whole-body configuration. After planning the footsteps, the dynamically stable whole-body motion including walking can be computed by using the method presented earlier.

Task-priority generalized inverse kinematics for redundant robots in Sect. 10.3 usually models tasks as equalities so that the operational points can achieve the desired velocity. However, tasks are sometimes given as inequalities: keeping the hand out of some area to avoid collisions or robot view obstruction, respecting joint limits, or maintaining the COM inside the foot support area. Inequality tasks have usually been transformed into more restrictive equality constraints through potential fields. A method for extending the task-priority inverse kinematics for those inequality tasks is proposed to remove this limitation based on a sequence of QP optimization [67.87]. This method searches for the optimal sets for the sequence of QPs by minimizing the error to the desired equality tasks in such a way that inequality ones can also be satisfied at a desired priority. This method allows the humanoid to perform such

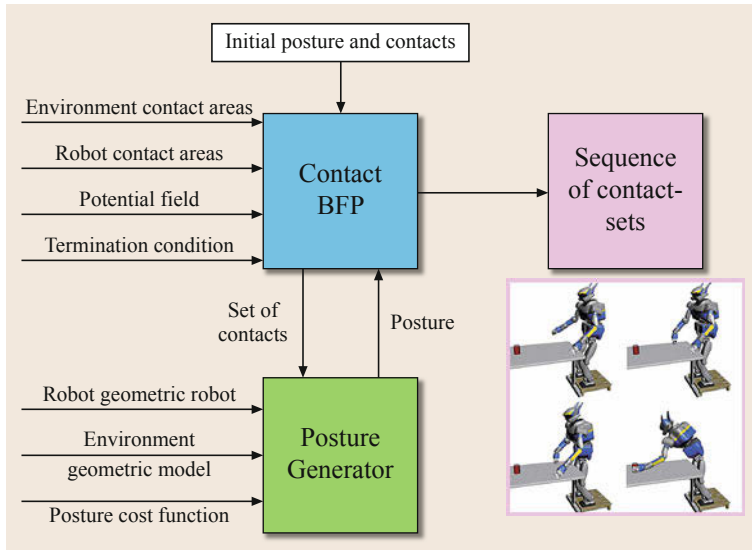


Fig. 67.36 Framework of contact motion planner composed of contact best-first-planner (BFP) and posture generator (after [67.107])



Fig. 67.37 A sequence of planned whole-body motion including multiple contacts on a irregular terrain (after [67.108])

a task of reaching its arm towards an object on the floor without obstructing its view.

This approach based on cascaded QP can be generalized to generate whole-body motions including dynamic equality and inequality tasks [67.109]. In addition to inverse kinematics considered so far, inverse dynamics is also integrated to the task-priority whole-body motion generation framework. By using this method, the dynamic balance can be addressed directly without converting the dynamic ZMP constraint into COM velocity via a pattern generator. This approach assumes a torque-controlled humanoid as opposed to position controlled ones that are often the case for platform currently used. However, dynamic whole-body motion generation with various tasks is being actively studied owing to not only recent progress of robot hardware [67.110] but also increasing interests on more complex tasks including multiple contacts presented in the next section.

67.5.4 Generating Motions Including Multiple Contacts

The whole-body motions presented so far basically supposes only the contacts between the humanoid's feet and the floor. Looking at our daily life however, contacts other than with feet occurs often, for example pass

through narrow spaces or to support the body when reaching a distant place on the desk. Since a humanoid is high affinity to environments designed for humans, its application fields could be expanded by exploiting the contacts as much as possible rather than by avoiding them as is often the case in motion planning. This section addresses planning and control of whole-body motions with multiple contacts that have been intensively studied in recent years. The role of planner is to derive a global sequence of configuration with multiple contacts to reach the goal, whereas the controller generates dynamically stable motions to transit from one contact state to another.

Motion Planning for Multiple Contacts

Multicontact nongaited have been proposed that are applicable to legged robots including humanoids [67.107, 108, 112]. By defining a stance as a finite set of contacts between the robot and the environment, the planner generates a sequence of stances that can reach the goal. During the planning, possible transitions from a stance are explored by sampling another stance with a feasible and stable robot configuration, as shown in Fig. 67.36 [67.107]. Figure 67.37 shows a resultant locomotion planned using this planning method [67.108]. A more generalized framework is proposed to deal with multirobot and multiobject systems [67.113]. This



Fig. 67.38 Dynamic multicontact motion generated through global trajectory optimization (after [67.111], VIDEO 597)

generalization allows for a common description and treatment of locomotion and manipulation problems, either for a single robot or for multiple collaborating robots.

The output of the planner is a sequence of statically stable contact stances that can be executed through quasi-static motions. In order to generate fast but dynamically stable motions, a global optimization approach has been proposed [67.111]. This method parameterizes joint trajectory by B-Spline function to convert the infinite trajectory problem to semi-infinite one so that optimization technique can be applied. The whole-body motion is generated through nonlinear optimization to minimize square torque and execution time, by taking into account such constraints as joint torque limits and dynamic multiple contact stability. As a result, the generated motion is much faster than quasi-static ones. An example of resultant motion is shown in Fig. 67.38 and VIDEO 597. Trajectory optimization approach can also be applied for lifting of a very heavy object by generating a weight-lifting motion by always respecting physical constraints [67.114].

Even though the feasibility of multicontact motions like in Fig. 67.38 have been validated with experiments, the optimization process is time-consuming and cannot cope with errors or disturbances during execution. It is therefore necessary to build a controller that ensures execution of multicontact whole-body motions.

Stability Measure for Motion with Multiple Contacts

Before discussing controller, it is worth mentioning first dynamic stability measure for non coplanar contacts and its usage. Although the ZMP is well-known dynamic stability criteria, it can only be applied to contacts on a flat plane. Stability margin for mobile robots [67.118] is only applicable for static gait for legged robots. A generalized version of ZMP (GZMP)

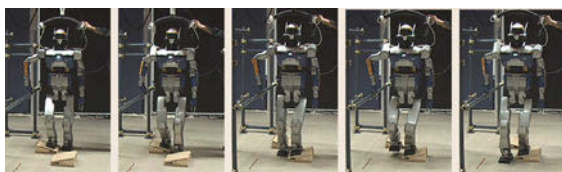


Fig. 67.39 Walking on a rough terrain using a support of arm on a handrail (after [67.115])

has therefore been proposed [67.119] by extending the ZMP by considering interaction forces other than floor-feet contacts. The stable region for multiple contacts can be obtained by considering the infinitesimal displacement and the moment about the edges of the convex hull of the supporting points. Hirukawa et al. proposed another criterion called contact wrench sum (CWS), which is the sum of the gravity and the inertia wrench applied to the COG of the robot. The humanoid is stable if it is inside the polyhedral convex cone of the contact wrench between the feet of a robot and its environment [67.115, 120]. Based on this criterion, walking

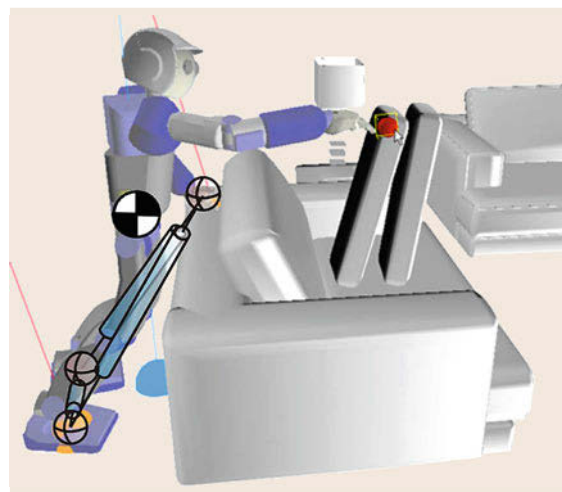


Fig. 67.40 Real-time simulation of a multicontact behavior with user-enabled interactive control of the robot's right hand. A virtual linkage model is overlaid capturing the internal force behaviors acting between supporting bodies (after [67.116])

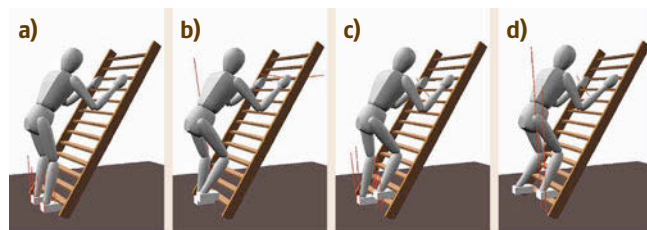


Fig. 67.41a–d A digital figure climbing a ladder by using whole-body controller with task priority with multiple contacts (after [67.117])



Fig. 67.42 Snapshots from multicontact planning and control of HRP-2 ingress in a car (after [67.121]). From the initial posture, supported on the steering handle and the seat by an arm, the robot finally succeeds in entering the car

on a rough terrain by supporting a handrail has been performed (Fig. 67.39).

Controlling Whole-Body with Multiple Contacts

The execution of the multicontact motions presented earlier by a humanoid requires the control based on sensor feedback to absorb unexpected disturbance or modeling errors.

Khatib et al. extended their framework of operational space approach that enables a humanoid robot to perform motions that simultaneously meet prioritized objectives in existence of multiple contacts [67.116, 117]. A torque-based approach for the control of internal forces is suggested and integrated into the framework for whole-body prioritized multitasking, thus enabling the unified control of COM maneuvers, operational tasks, and internal-force behavior (Fig. 67.40). Figure 67.41 shows an example of multicontact behavior on a real-time simulator. *Hyon* et al. proposed another approach of passivity-based controller that can

adapt to unknown external forces applied to arbitrary contact points without sensing the contact forces by using a torque-controlled robot [67.122].

Another real-time controller based on linear QP optimization has been proposed for whole-body motion with multiple contacts [67.121, 123]. The motion is constrained by the free-floating whole-body dynamics of the humanoid robot without using a reduced model such as inverted pendulum since the motions we aim at are more general than bipedal walking. The optimization process also incorporates such constraints as nonsliding condition, actuation torque limits, contact forces within friction cones, and avoidance of undesirable self-collisions and collisions with the environment. Taking a target contact stance and also necessary sensory information as its input, the controller can compute feedback control commands to execute the whole-body motion with multiple contacts in real time, on less than 100 Hz control loop. Figure 67.42 shows a simulation result of complex motion of a humanoid entering into a car based on the control method.

67.6 Morphological Communication

Humans evaluate each others' state through body posture and movement. It is quite natural to extend this form of communication to include robots that share our morphology.

67.6.1 Expressive Morphology and Behavior

Humanoids can communicate with people through expressive morphology and behavior. As with people, humanoid robots integrate communicative and noncommunicative functionality. For example, the arms and hands of a robot can reach and grasp, but also point and gesture. Heads for humanoid robots are an especially important example of these overlapping roles, and have had an important impact on humanoid robotics and robotics in general [67.124].

The head of a humanoid robot has two main functions:

- To orient directional sensors as needed for the purposes of perception, while leaving the main body free to meet other constraints such as maintaining balance and gait. Cameras and sometimes microphones are usefully oriented in this way.
- To strike expressive poses, along with the rest of the body. Even if a robot head is not intended to be expressive, it will be interpreted as being so by humans – particularly as a cue to the robot's presumed locus of visual attention. It is also possible to deliberately engineer an approximate *face* that can be an important line of communication with humans (Chap. 72).

Locus of Attention

Eyes can be one of the most expressive components of a humanoid robot. For humans, eye movements are both expressive and important for sensing. Humanoid robots

have the option to factor these two roles by moving eyes that are only for display, and using sensors placed elsewhere. Most humanoid robots, however, use head-mounted servoed cameras that play both expressive and sensory roles. These mechanisms exhibit different degrees of biological realism, for example, the Kismet head captured many of the expressive components of human eye movements, while having a nonhuman-like camera arrangement that simplified some forms of perception (Fig. 67.43).

Many humanoid robots use biologically inspired, foveated vision systems, which provide a wide field of view with low detail, combined with a narrow field of view with high detail (Fig. 67.44). With appropriate control strategies to fixate the narrow field of view on task-salient regions detected in the wide field of view, these robots achieve a practical compromise between resolution and field of view. Additionally, the configuration of the eyes communicates the robot's locus of attention in an intuitive way. Many systems use four cameras, with a narrow- and wide-angle camera for each of the robot's eyes, but some researchers have also used special-purpose space-variant cameras modeled after the space-variant receptor densities in the human eye [67.125].

The eye movements of some humanoids are modeled explicitly after human eye movements. An example of a model of this kind is shown in Fig. 67.45. These

bio-inspired approaches to active vision typically have four types of visual behavior:

Saccades. These are high-velocity movements to fixate a new target or *catch up* with a fast-moving target. From a control point of view, these movements are *ballistic* (at least in humans) – once initiated, they continue without responding to changing stimuli.

Smooth Pursuit. These are movements to continuously track a moving target. They apply at low velocities. These movements respond constantly to visual feedback about the target's location. A fast-moving target may also trigger small saccades.

VOR and OKR. The vestibulo-ocular reflex and optokinetic response work to stabilize the direction of gaze in the presence of movement of the head and body, using inertial and visual information respectively.

Vergence. This movement drives the relative angle of the two eyes so that the same target is centered in both. This only applies to two-eyed systems that have this freedom of motion. For conventional stereo algorithms,

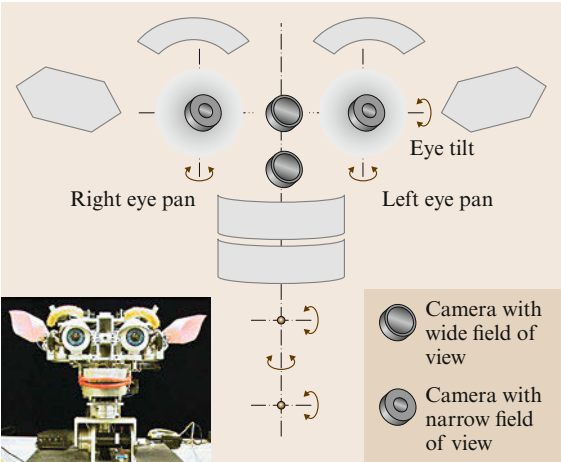


Fig. 67.43 On Kismet, foveal vision was implemented using cameras in the eyes, and peripheral vision used unobtrusive cameras on the head (after [67.124]). This achieved good expression of locus of attention, while simplifying the process of differentiating egomotion from motion of objects (since the head moved less frequently and more slowly than the eyes). This is an example of a partial decoupling of expressive and functional concerns, showing that many different levels of humanoid *fidelity* are possible

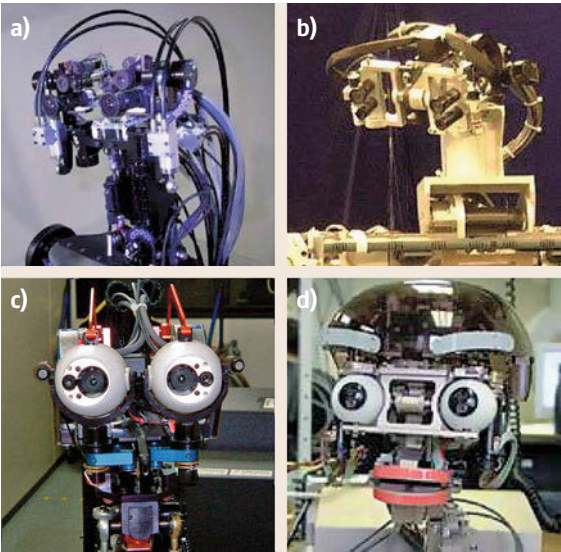


Fig.67.44a–d The heads of humanoid robots come in many forms. A popular arrangement is to have two cameras per eye, as a crude approximation of foveal and peripheral vision in humans. (a) Biomimetic oculomotor control investigated on DB (after [67.126]). (b) Cog's head (after [67.127]). (c) The double-camera arrangement can be arranged in a less-double-barreled appearance (after [67.128]; see Ude et al. [67.128] for more examples and an analysis) ATR; Humanoid head developed by ATR and SARCOS. (d) The Infanoid robot (after [67.129])

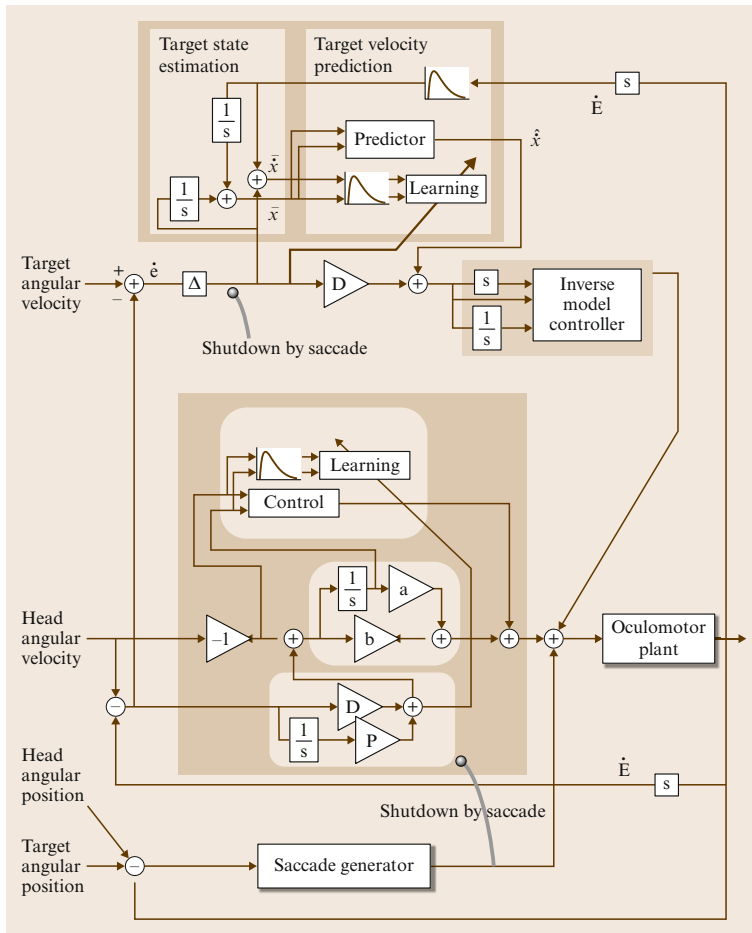


Fig. 67.45 A biomimetic control model (after [67.130]), that integrates saccading, smooth pursuit, the vestibular-ocular reflex (VOR), and the optokinetic response (OKR). Smooth pursuit and VOR/OKR commands are summed, with periodic corrections to errors in position made by saccades

vergence is a disadvantage, since the algorithms are simplest when the cameras remain parallel. Other algorithms are possible, but it is currently quite common not to use vergence.

67.6.2 Interpreting Human Expression

The interpretation of human expression is essential for many forms of natural human communication that could be valuable for humanoid robots.

Posture and Expression

The recognition and interpretation of the location and pose of humans is important, since humanoids are often expected to work in human environments. Algorithms for the following functions have been incorporated in various humanoids:

- Person finding
- Person identification

- Gesture recognition
- Face pose estimation.

ASIMO has used these functions to perform a prototypical reception task as shown in Fig. 67.46. The robot can find and identify a person, then recognize gestures such as *bye-bye*, *come here*, and *stop*, which are utilized for performing reception tasks. In general, such func-

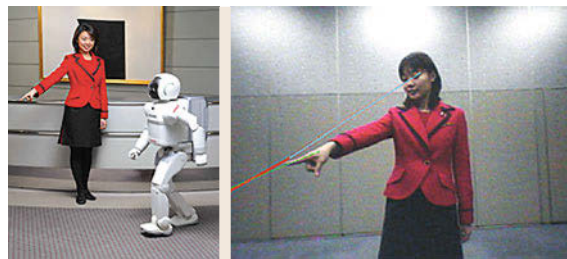


Fig. 67.46 ASIMO recognizing a pointing gesture during a reception task

tions on a humanoid are not yet robust, and are active areas of research.

Speech Recognition

Speech is a natural, hands-free mode of communication between humans, and potentially between robots and humans. Speech recognition is a popular interface utilized for commanding a humanoid, and many off-the-shelf packages are now available. However the use of microphones embedded in the robot is problematic, because general-purpose speech recognition software is usually optimized for utterances captured by a microphone that is close to the speaker. In order to achieve sufficient recognition performance in natural interaction situations between a humanoid and a human new methods for speech recognition are being investigated. These methods compensate for sources of noise, such as the robot's motors and air flow in the environment, by using multiple microphones and multimodal cues [67.131]. However, at the time of writing researchers often circumvent these issues by using a headset, lavalier, or handheld microphones.

Auditory Scene Analysis

In order to attain more-sophisticated human-robot interaction, researchers have been developing methods for computational auditory scene analysis on a humanoid robot. The objective of this research is to understand an arbitrary sound mixture including nonspeech sounds and voiced speech, obtained by microphones embedded in the robot. Beyond speech recognition, this also involves sound-source separation and localization.

As for sound recognition, sound categories such as *coughing*, *laughing*, *beating by hand*, *adult's voice*, and *child's voice* have been shown to be recognizable using maximum-likelihood estimation with Gaussian mixture models. This function has been utilized during interactions between the HRP-2 and a human [67.132].

Multimodal Perception

Sound-source separation can be achieved by beam forming. In order to perform beamforming effectively, sound-source localization is essential. Vision can be utilized for finding the talker within the field of view. Hara et al. used a camera and an eight-channel microphone array embedded in the head of HRP-2, and succeeded in speech recognition in the presence of multiple sound sources by using sound source separation [67.133]. Figure 67.47 shows a scenario in which speech recognition is taking place with television (TV) sound playing in the background.

When integrated with speech recognition, vision can also help resolve the ambiguities of speech. For instance, the ambiguity of demonstrative pronouns such

as *this* or *that* can sometimes be resolved by recognizing pointing gestures. Similarly, the face and gaze direction can be used to realize communication via eye contact, so that the humanoid only replies when a human is looking at it and talking to it [67.132]. Multimodal interaction with these functions has also been demonstrated by HRP-2, as shown in Fig. 67.48.

67.6.3 Physical Interaction and Developmental Robotics

Humanoid robots typically use methods for perception and interaction that are established in fields such as computer vision and dialogue systems. There is also an emerging research field called developmental robotics or epigenetic robotics in which human-like perception and interaction abilities are obtained through physical interaction with the real environments including humans [67.134–136]. In developmental robotics, researchers aim at studying the developmental mechanisms, architectures and constraints that allow life-long and open-ended learning of new skills and new knowledge in embodied machines. Much of the research in this field utilizes humanoid robots, such as the iCub shown in Fig. 67.36. As in human children, learning is expected to be cumulative and of progressively in-



Fig. 67.47 HRP-2 recognizing speech with background noises (TV sound)



Fig. 67.48 HRP-2 recognizing face and gaze direction for communication via eye contact

creasing complexity, and to result from self-exploration of the world in combination with social interaction. The typical methodological approach consists in starting from theories of human development elaborated in fields such as developmental psychology, cognitive science, neuroscience, developmental and evolutionary bi-

ology, and linguistics, then to formalize and implement them in robots. The experimentation of those models in robots allows researchers to confront them with reality, and as a consequence developmental robotics also provides feedback and novel hypothesis on theories of human development.

67.7 Conclusions and Further Reading

Because of the integrative nature of humanoid robotics, this chapter has avoided details and formalisms and liberally cross-referenced other chapters within the handbook that can provide the reader with deeper coverage of many of the areas of robotics on which humanoid robots depend. Additionally, this chapter references work within the humanoid robotics community and related communities.

Humanoid robotics is an enormous endeavor. The emulation of human-level abilities in a human-like robot serves as a grand challenge for robotics, with significant cultural ramifications. The motivations for humanoid robotics are as deep as they are diverse. From the earliest cave drawings, humanity has sought to represent itself. Robotics is one of the most recent mediums for this ongoing fascination. Besides this deep societal motivation, hu-

manoid robots offer unique opportunities for human-robot interaction, and integration into human-centric settings.

Over the last decade, the number of humanoid robots developed for research has grown dramatically, as has the research community. Humanoid robots have already gained a foothold in the marketplace as robots for entertainment and research (e.g., the Robo-One competition and the NAO from Aldebaran). Given the special properties of humanoid robots, they seem likely to further increase in number as their capabilities improve and their costs go down. Robots with human characteristics, and technologies related to humanoid robotics, also appear destined to proliferate. Will human-scale, legged robots with human form become commonplace, as so often imagined by science fiction? Only time will tell.

Video-References

-  **VIDEO 594** 3-D collision-free motion combining locomotion and manipulation by humanoid robot HRP-2 available from <http://handbookofrobotics.org/view-chapter/67/videodetails/594>
-  **VIDEO 595** Whole-body pivoting manipulation available from <http://handbookofrobotics.org/view-chapter/67/videodetails/595>
-  **VIDEO 596** Footstep planning modeled as a whole-body inverse kinematic problem available from <http://handbookofrobotics.org/view-chapter/67/videodetails/596>
-  **VIDEO 597** Dynamic multicontact motion available from <http://handbookofrobotics.org/view-chapter/67/videodetails/597>
-  **VIDEO 598** 3-D collision-free motion combining locomotion and manipulation by humanoid robot HRP-2 (experiment) available from <http://handbookofrobotics.org/view-chapter/67/videodetails/598>
-  **VIDEO 599** Regrasp planning for pivoting manipulation by a humanoid robot available from <http://handbookofrobotics.org/view-chapter/67/videodetails/599>
-  **VIDEO 600** Footstep planning modeled as a whole-body inverse kinematic problem (experiment) available from <http://handbookofrobotics.org/view-chapter/67/videodetails/600>

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68. Human Motion Reconstruction

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This chapter presents a set of techniques for reconstructing and understanding human motions measured using current motion capture technologies. We first review modeling and computation techniques for obtaining motion and force information from human motion data (Sect. 68.2). Here we show that kinematics and dynamics algorithms for articulated rigid bodies can be applied to human motion data processing, with help from models based on knowledge in anatomy and physiology. We then describe methods for analyzing human motions so that robots can segment and categorize different behaviors and use them as the basis for human motion understanding and communication (Sect. 68.3). These methods are based on statistical techniques widely used in linguistics. The two fields share the common goal of converting continuous and noisy signal to discrete symbols, and therefore it is natural to apply similar techniques. Finally, we introduce some application examples of human motion and models ranging from simulated human control to humanoid robot motion synthesis.

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68.1 Overview

Human motions are valuable resources for robots as they implicitly represent human strategies for control and planning. They are particularly useful when the control objective is difficult to formulate as a cost function, such as conveying expressions or moving in a particular style. Many researchers have used human motions for teaching new tasks to robots [68.1] and generating robot motions with human-like styles [68.2].

In order to use human motions for robotics applications, we first have to reconstruct the motion from raw measurement from a motion capture system. For this

purpose, we can apply many techniques and algorithms developed in robotics such as kinematics, dynamics, parameter identification, and statistical models. In some applications such as robot learning, reconstructed motion data represented as sequences of joint angles are often not useful. In this case, the motion must be interpreted as higher level representation such as a sequence of behaviors.

This chapter reviews some of the algorithms for reconstructing and interpreting human motions for robotics applications. The next section describes the

kinematic and dynamic computations for human motion reconstruction. As these algorithms were originally developed for robot manipulators, we need substantial adaptation to human body due to its complexity. In Sect. 68.3, we present an overview of statistical approaches for understanding human motions as discrete behaviors, and use them for communication between

humans and robots. The technique presented here has a close relationship to natural language processing that deals with the similar problem of converting continuous signal (sound) to discrete symbols (words). Finally, we review a few examples of using human motions to generate human-like motions on virtual humans as well as humanoid robots.

68.2 Models and Computations

Motion capture refers to measuring motions in the Cartesian space. The subjects are usually humans but animals or robots may also be used. Many motion capture technologies are commercially available with varying costs and capabilities. We will give a brief overview of the most popular motion capture systems: optical and mechanical.

68.2.1 Motion Capture Technology

Optical Motion Capture

Optical motion capture systems are popular thanks to the minimum disruption to motions, although high-end systems can be expensive because of high-resolution, high-speed cameras and elaborate software. Furthermore, offline data cleanup is often necessary to handle occasional occlusion and mislabeling. These systems are widely used in many fields including biomechanics, entertainment, and robotics.

Figure 68.1 shows the principle of optical motion capture. Multiple markers (white circles) are attached to the subjects' body (gray) as *landmarks* to be detected by the cameras surrounding the capture area. The three-dimensional (3-D) marker positions are obtained by computing the intersection of lines connecting the cameras' optical center and the markers on the image plane.

Human whole-body motion capture typically requires more than 40 markers. The markers are usu-

ally spherical and retro-reflective, which means that they reflect the incoming light directly back to the light source. The subject experiences very little disruption during motions because the markers are light and small, although they can be a problem in motions that involve physical contacts with other subjects or the environment.

The capture area is surrounded by three or more cameras with near-ultraviolet light source. Because the markers are retro-reflective, they can be easily detected in the camera images as bright disks by simple image processing with little effect from the lighting condition. The internal and external camera parameters are identified through a system-specific calibration process before each motion capture session.

Human motions are reconstructed in three steps. First, the markers are detected from the camera images. Then the Cartesian positions of the markers can be computed by using the marker positions from multiple cameras. Finally, joint angle data are computed by performing inverse kinematics computation (👁️ VIDEO 762). This step will be described in Sect. 68.2.2.

The complexity of the software is due to the three-dimensional (3-D) reconstruction process where it is difficult to identify the correspondence between the markers in multiple images because all markers look identical. Furthermore, some of the markers may be lost due to occlusion and fast motions. In practice, careful marker and camera placement is required to obtain consistent measurements.

Mechanical Motion Capture

Another family of motion capture technology is mechanical, where a mechanical device is attached to the subject's body to directly measure the joint angles. Earlier systems used mechanical linkages consisting of rigid links and joint angle sensors, which were bulky and therefore significantly restricted the subjects' mobility. However, more recent systems use flexible suits with embedded bend sensors that do not cause as much restriction. The suits are equipped with additional inertial sensors to measure the global position.

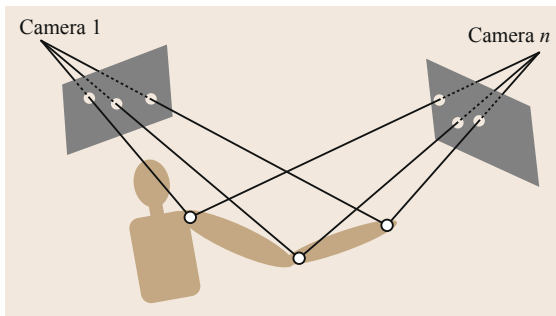


Fig. 68.1 Principle of optical motion capture

An advantage of this technology is that it can directly measure the joint angles, and therefore is more robust than optical systems. It also allows unbounded capture area, possibly in outdoor environments. On the other hand, the inertial sensors used for measuring the global motion of the body may suffer from drifts that result in inaccurate global position measurements. Drifts are usually corrected assuming that at least one of the foot segments is fixed to the environment, but this is not the case in motions involving flights.

Future of Motion Capture

Development of markerless, realtime, and low-cost motion capture systems is an active research area in both academia and industry. In fact, several commercial products with some of those features are becoming available.

For example, the OpenStage system [68.3] from Organic Motion realizes realtime markerless motion capture. Kinect [68.4] has been developed for gaming interface but it can potentially be used as a low-cost, realtime motion capture system. Some researchers are working on even more challenging motion capture techniques, such as markerless motion capture using monocular vision [68.5].

68.2.2 Skeleton Model and Computation

Once motion capture data are obtained, we can analyze the data by computing the joint angles and torques, provided that kinematics and dynamics models of the subject are available. While a number of algorithms have been developed for motion analysis and simulation of robots, applying these algorithms to the human body is not straightforward.

The human body is much more complex than most mechanical systems. It consists of a number of elements such as bones, muscles, organs, and skin, most of which are deformable and difficult to model themselves. Many joints are also difficult to model and simulate because of the complex constraints. For example, the center of rotation of the shoulder joint moves along with the joint movement. The knee and elbow joints are constrained by rolling contacts and ligaments between bones.

In practice, therefore, it is unrealistic to model all the details due to computational complexity, and the human body is typically approximated by articulated rigid body models familiar to the robotics community. We can then apply the kinematics and dynamics algorithms for mechanical systems as described in this subsection. Figure 68.2 shows an example of detailed human skeleton model [68.6], which consists of 155 degrees of freedom (DOF) excluding the fingers.

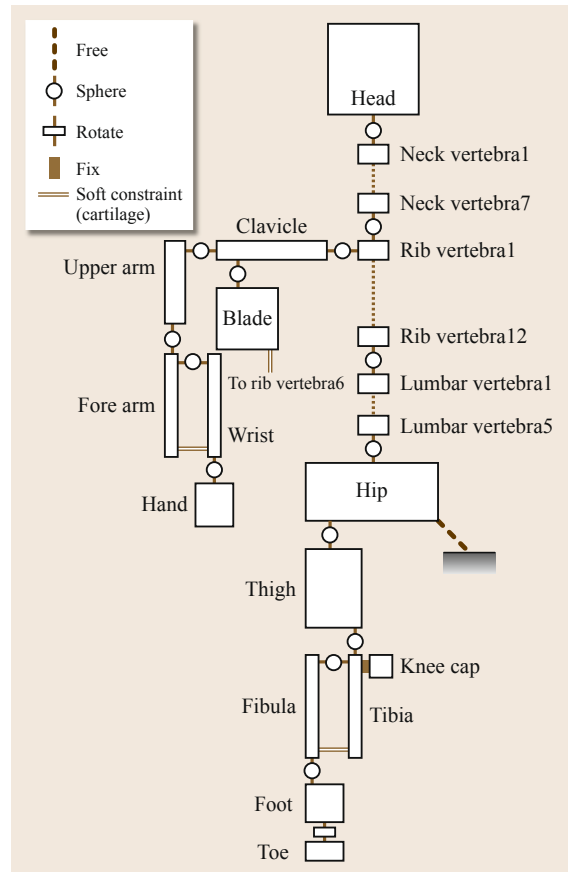


Fig. 68.2 Detailed human skeleton model

Even if we use simplified skeleton models, there is still an issue of obtaining accurate model parameters. As mentioned above, many joints do not have a fixed axis as in mechanical joints, which means that the kinematic parameters such as link length may not be constant as in mechanical systems. It is also difficult to estimate the inertial parameters because we cannot directly measure the individual link parameters, and because the human body is flexible and some of the soft tissue would move between links. We will discuss the parameter identification issue in Sect. 68.2.4.

Kinematics

Inverse and forward kinematics computations are used to analyze the kinematic quantities of measured motions such as positions, velocities, and accelerations of the links.

Inverse kinematics computation is critical to data obtained by optical motion capture because we have to convert the marker positions to skeleton joint angles. Typical inverse kinematics problem in robotics (Chap. 2) is to compute the joint angles given the

end-effector position and/or orientation. Inverse kinematics for motion capture data processing needs a slightly different problem setting because many markers are attached throughout the body, often resulting in an over-constrained system. Furthermore, measured marker positions would not perfectly fit an articulated rigid body model because human kinematics parameters may change during the motion, as discussed above.

A simple method for computing the joint angles, often used as the default method in commercial optical motion capture systems, is to first compute the joint centers by interpolating the positions of a few strategically placed markers, and then computing the joint angles from the joint centers. The advantage of this method is that it is easily customizable by, for example, simple scripts and therefore suitable for commercial systems.

Another method is to apply numerical optimization. For example, the cost function can be the sum of squared distances between the marker positions from the measurement and those computed by the kinematics model. Another approach is to *drive* the model toward the measured marker positions [68.7]. In either case, the resulting joint angle will evenly distribute the error caused by measurement error and model inaccuracy to all markers.

Figure 68.3 shows an example of inverse kinematics using a skeleton model.

Forward kinematics is performed to obtain the Cartesian positions, velocities, and accelerations of the links from the corresponding joint variables. These quantities are often used for the dynamics computation later.

Dynamics

Similarly to kinematics computation, we can consider both inverse and forward dynamics.

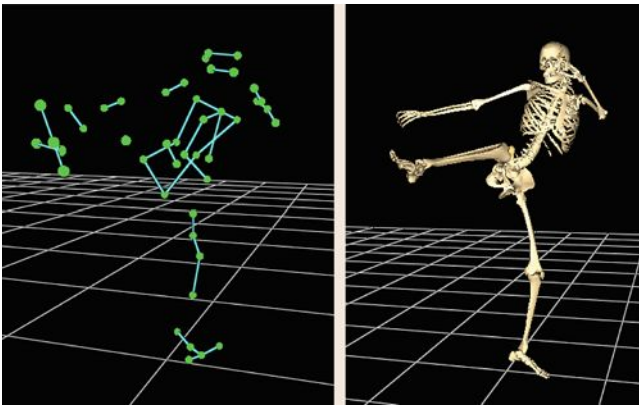


Fig. 68.3 Inverse kinematics computation example

Inverse dynamics computes the joint torques and possibly contact forces required to perform the measured motion. Any algorithm for inverse dynamics computation of articulated rigid bodies, such as the Newton–Euler formulation [68.8], can be applied. Chapter 3 gives the details on dynamics algorithms for general kinematic chains.

A major difference from manipulator inverse dynamics is that the human body is a floating-base system where the root joint can move freely in the six-dimensional (6-D) space but is not actuated. Generic inverse dynamics algorithms for manipulators give the 6-D force and torque for the root joint but they are not actually available. The equivalent force must be supplied instead by the contact forces, which have to be explicitly considered because they affect the joint torques.

The equation of motion of an n -DOF articulated rigid body system is written as

$$\tau_G = \mathbf{M}(\theta) \ddot{\theta} + \mathbf{c}(\theta, \dot{\theta}) + \mathbf{g}(\theta), \quad (68.1)$$

where $\tau_G \in \mathbb{R}^n$ is the generalized force, $\theta \in \mathbb{R}^n$ is the generalized coordinate, $\mathbf{M} \in \mathbb{R}^{n \times n}$ is the joint-space inertia matrix, $\mathbf{c} \in \mathbb{R}^n$ represents the centrifugal and Coriolis forces, and $\mathbf{g} \in \mathbb{R}^n$ is the gravitational force. In human body models subject to m contact constraints, τ_G is computed from active joint torques $\tau \in \mathbb{R}^{n-6}$ and contact forces $\mathbf{f}_c \in \mathbb{R}^m$ as

$$\tau_G = \mathbf{S}^T \tau + \mathbf{J}_c^T \mathbf{f}_c, \quad (68.2)$$

where $\mathbf{J}_c \in \mathbb{R}^{m \times n}$ is the Jacobian matrix of the contact constraints and $\mathbf{S}^T \in \mathbb{R}^{n \times (n-6)}$ is the matrix that converts the active joint torques to generalized forces. Without losing generality, we assume that the root joint corresponds to the first six elements of the generalized coordinate. Then $\mathbf{S}^T$ takes the form

$$\mathbf{S}^T = \begin{pmatrix} \mathbf{O}_{6 \times (n-6)} \\ \mathbf{I}_{(n-6) \times (n-6)} \end{pmatrix} \quad (68.3)$$

where $\mathbf{O}_*$ and $\mathbf{I}_*$ are the zero and identity matrices of the sizes given by the subscripts.

The number of constraints m changes depending on the contact condition. If, for example, both feet are in flat contact with the ground, m would be 12 because the position and orientation of each foot are constrained.

Equations (68.2) and (68.3) indicate that only $\mathbf{f}_c$ contributes to the first six elements of τ_G . This property corresponds to the well-known fact that the whole-body momentum can be changed only by applying external forces such as contact forces. We can utilize this fact to compute $\mathbf{f}_c$ independently of the joint torques [68.6].

We can then compute the joint torques using the bottom $(n - 6)$ equations of (68.2).

Forward dynamics is used for dynamics simulation. The simulation in this context usually involves a set of controllers that attempts to make the human model track the measured motion. This computation is often performed to simulate the effects of external disturbances and physical disabilities. However, developing controller for human body simulation is very difficult because the root joint is not actuated and the contact forces are subject to unilateral constraints. Although this topic is extensively discussed in humanoid robotics, graphics, and biomechanics, there is no consensus on how to build general controllers for human models.

68.2.3 Musculoskeletal Model and Computation

Motion analysis based on skeleton models is not sufficient for applications that require anatomical information such as muscle lengths and tensions. In biomechanics, for example, researchers are often interested in computing the muscle tensions required to perform a motion. Also in robotics, many muscle-like actuators are developed and used to design more human-like robotic systems.

Musculoskeletal models are used for motion analysis involving muscles. In addition to a skeleton model discussed in the previous section, a musculoskeletal model includes a musculotendon network model that describes where the muscles are attached to and how

they are routed around the bones. Similarly to skeleton models, musculotendon network models include a number of simplifications due to the complexity of the real human body. A muscle is usually modeled as a line segment that produces a uniform tensile force. Interactions of muscles with bones and skin are not usually modeled except for some of the major muscle–bone interactions.

Apart from these simplifications, the force interaction between the muscles and bones are described as accurately as possible. A simple muscle–tendon pair connects two bones and produces a torque at the joint between them (Fig. 68.4a). More complex muscles may pass through one or more points fixed on the bone surface (Fig. 68.4b), or may have branches and therefore connects three or more bones. Wide muscles, such as pennate muscles, are modeled by several parallel muscles.

Figure 68.5 shows a detailed musculoskeletal model consisting of 955 muscles [68.6].

Kinematics computation on a musculoskeletal model gives the muscle lengths. The length and its velocity may then be used for various analysis. For example, we can use Hill–Stroeve muscle model [68.9, 10] to compute the maximum muscle tension.

The active joint torques τ are now produced by muscle tensions f_m . Applying d’Alembert’s principle, we can derive the relationship between τ and f_m as

$$\tau = J_m^T f_m, \quad (68.4)$$

where J_m is the Jacobian matrix of the muscle lengths with respect to the generalized coordinates.

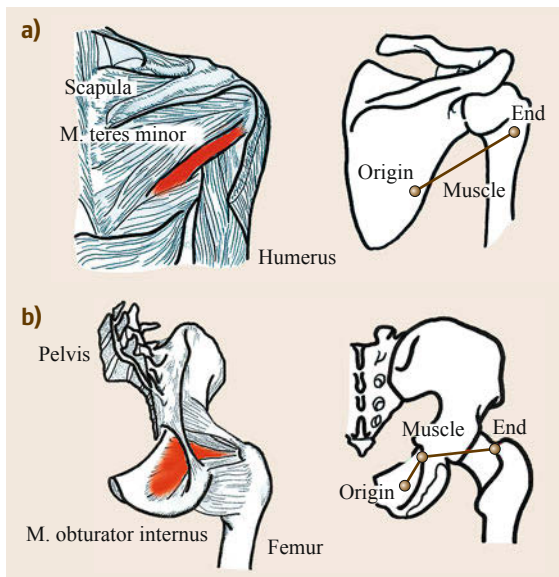


Fig. 68.4a,b Examples of muscle models; (a) simple wire connecting two bones, (b) muscle with via point

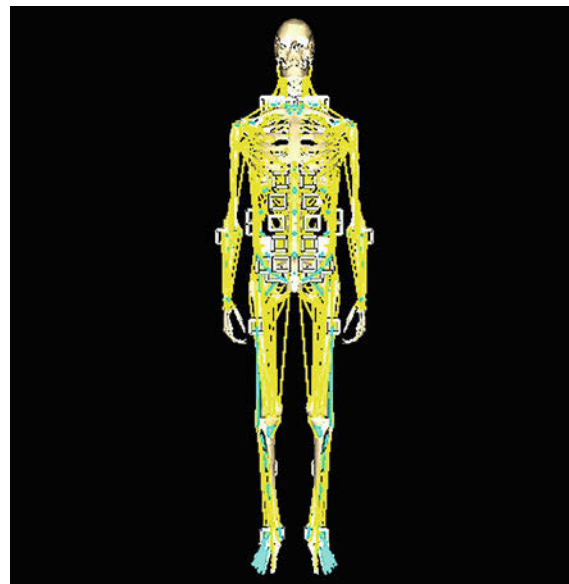


Fig. 68.5 A detailed musculoskeletal model

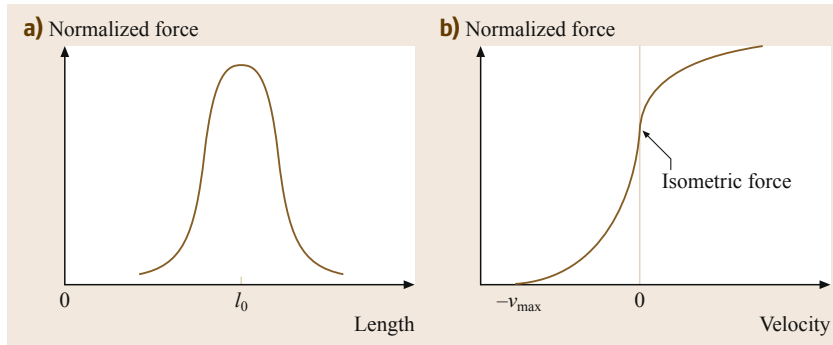


Fig. 68.6a,b Relationship between maximum muscle tension and muscle fiber length. **(a)** Length–tension relationship, **(b)** velocity–tension relationship

The inverse dynamics computation for musculoskeletal models is summarized as follows:

1. Compute the joint angles, velocities, and accelerations of the motion capture data.
2. Compute the joint torques τ of the skeleton model.
3. Map the joint torques to muscle tensions using (68.4) (VIDEO 763).

Because most musculoskeletal models contain more muscles than the skeleton DOF, the final step does not have a unique solution. The muscle tensions also have to be constrained to be tensile. A common approach for this problem is to apply numerical optimization techniques [68.6, 11]. However, actual muscle tensions may not be optimal because of the phenomena called co-contraction, where antagonistic muscles are activated at the same time. Such effect can be incorporated by measuring the muscle activity through electromyography (EMG) and consider the data in optimization [68.12].

Another method for computing muscle tensions is to utilize physiological muscle models. The most commonly used model was originally proposed by Hill [68.9] and later formulated by Stroeve [68.10].

Muscle tension f is characterized by three components: muscle activity a , muscle length l , and change of muscle length $\dot{l}$ as follows:

$$f = a F_l(l) F_v(\dot{l}) F_{\max}, \quad (68.5)$$

where $F_{\max}$ is the muscle-specific maximum voluntary force, $F_l(*)$ and $F_v(*)$ are the functions that represent length–tension and velocity–tension relationship respectively (Fig. 68.6). The muscle activity a changes according to the following differential equation,

$$\dot{a} = \frac{u - a}{T}, \quad (68.6)$$

where T is a time constant and u is the normalized input from the motor neuron which can be measured by EMG.

68.2.4 Model Identification

Obtaining accurate human model parameters is difficult but very important for accurate motion and force estimation. For robots, we can build a model based on CAD (computer-aided design) models or even measurements of the individual link mass, but both are impossible for humans. On the other hand, personalized models are important to make the analysis results useful for individuals.

Identification of Kinematic Parameters

In human motion analysis, the set of joints constructing a human model is usually given. Kinematic parameters include distance between joints and direction of the joint axes.

We can apply some of the kinematic parameter identification techniques for robots [68.13] using motion capture to provide the data necessary for identification. Another approach is to use a human dimension database [68.14] and use a few measurements from the subject to estimate the rest.

Identification of Inertial Parameters

Conventional methods for manipulator inertia parameter identification (Chap. 6) use joint torque data, and therefore cannot be applied to the human body.

However, Ayusawa et al. [68.15] proved that contact force data give enough information to estimate the same set of parameters for floating-base models. As shown in Chap. 6, the generalized force τ_{Gi} required to perform a given motion described by the generalized coordinates θ_i , velocities $\dot{\theta}_i$, and accelerations $\ddot{\theta}_i$ is written as a linear equation of the identifiable inertial parameters p as

$$\mathbf{I}_i(\theta_i, \dot{\theta}_i, \ddot{\theta}_i) p = \tau_{Gi}. \quad (68.7)$$

We can obtain a number of these samples from motion capture data. In manipulators with joint torque sensors, all elements of $\mathbf{I}$ and τ_G are available and therefore it is trivial to solve (68.7).

As shown in (68.2), the generalized forces for human body models are produced by active joint torques and contact forces. From (68.3), (68.7) can be divided into the first six rows and the remaining $(n-6)$ rows as

$$\mathbf{I}_{ji}(\boldsymbol{\theta}_i, \dot{\boldsymbol{\theta}}_i, \ddot{\boldsymbol{\theta}}_i)\mathbf{p} = \mathbf{J}_{cji}^T \mathbf{f}_{ci}, \quad (68.8)$$

$$\mathbf{I}_{ai}(\boldsymbol{\theta}_i, \dot{\boldsymbol{\theta}}_i, \ddot{\boldsymbol{\theta}}_i)\mathbf{p} = \boldsymbol{\tau}_i + \mathbf{J}_{caif}^T \mathbf{f}_{ci}. \quad (68.9)$$

For human body, joint torque data $\boldsymbol{\tau}_i$ are not available. However, we can obtain the contact force data from force sensors embedded in the floor. In this case, we have all the information in (68.8). Ayusawa et al. [68.15] proved that this equation is enough for identifying the same set of parameters as using the full set of (68.7).

68.3 Reconstruction for Understanding

Human motion data can be used for motion and task learning for humanoid robots, as represented by imitation learning or learning by demonstration [68.1].

68.3.1 Segmentation of Human Motion

Human motion data are converted to a sequence of configurations, such as joint angles or link positions over the whole of the robot's body, and the sequence is encoded into a set of model parameters as the motion primitive. This encoding should follow the motion segmentation; a chunk of motion should be obtained by finding the frames where the motion starts and terminates in the seamless motion data. Manually selected motion segments are intuitive, reliable, and easily assigned their relevant motion labels. However, manual segmentation is limited by its lack of scalability for the large numbers of human motions required for training. Human motion should be segmented so that a humanoid robot can observe human actions and incrementally memorize the motion primitives by segmenting and encoding unknown motions.

In the supervised segmentation method, the relation between each motion frame and its boundary score from the training dataset is learned, and the boundary in the motion observation is identified. For the training dataset, human subjects have to detect the motion boundaries. Supervised segmentation has the same drawback in scalability to large motion datasets as manual segmentation.

There are studies of unsupervised segmentation based on various methods: stopped moment, motion clustering, and motion prediction. Motion segmentation based on the stopped moments is very simple. This segmentation assumes that a motion pattern transits to another motion via the stopped moment. The simplest strategy only has to find a pose when either joint stops as a boundary candidate. The extensive approach approximates a temporal sequence of the boundary candidates by a periodic function as a reference for the motion boundaries. These methods may work for rhythmic movements, such as dance, but it is not clear

whether they would be useful for segmenting daily human actions [68.16, 17].

Stochastic graphical models, typified by hidden Markov models (HMM), are used to model the stream of motion data [68.18]. An optimal node in the graphical model that is the most likely to generate the current motion observation can be calculated. The observations classified into the same node consequently are considered to be the same motion. In other words, the transition between two nodes corresponds to the boundary of the motions [68.19].

In natural language processing, word segmentation is critical, especially for speech recognition, in which words must be selected from a stream of phonemes. Predictability strategy hypothesizes that it is difficult to predict the character at the beginning of the word. A recurrent network based on this strategy has been applied to the segmentation of words [68.20]. The network learns the sequence of characters, and consequently predicts the character from its preceding one. This predictor detects a boundary where the error between the predicted and actual character becomes large, and subsequently selects words. Similar to this approach, during motion learning motion is converted to a sequence of short movements, each of which is represented by a binary vector equivalent to a word, and this sequence is trained as the correlation matrix. This matrix can be easily used to predict the short movement by multiplying this matrix by the vector of the preceding movement [68.21]. Movements with a large prediction uncertainty can be detected as the motion boundary.

68.3.2 Categorization of Human Motion

Human motion data is encoded into a set of parameters in the dynamical systems [68.22, 23] or stochastic models [68.24, 25]. The dynamical system representing state transitions by nonlinear differential equations is a popular way to encode human motions and subsequently synthesize robot motion adapted to various environments. The dynamics in the human motions is

defined as a vector field, and each motion pattern is expressed by a closed curve in this field, which is constructed so as to attract robot's motion to the reference motion [68.26]. This attractor field will stabilize the robot's motion even when the robot is perturbed by the external environment. A popular approach based on the dynamical system is a framework of the dynamic movement primitives (DMPs) [68.27]. This framework learns a single trajectory by using a spring-damping model including a forcing term which makes it easy to control a robot motion reaching a goal configuration. This framework has been extended to learn multiple human motions such that the robot can perform various motions and demonstrate the highly scalable nature [68.28]. These dynamical systems mainly focus on synthesize and control robot motions adaptively to the environment. While they can predict motions and classify the observation into its specific motion category, but they are not directly used for motion classification. Another popular approach based on the dynamical system is a recurrent neural network (RNN). The RNN generates the human posture following the input current one, and is optimized such that error between the generated posture and measured one can be minimized. The resultant RNN can be useful for the motion predictor. The RNN has been extended to a modified structure with a layer of the small number of parametric biases, into which the dynamics in the human motion can be encoded [68.29]. This structure has an advantage of not only generating motions from perception, but also recognize the perception as a category defined by these biases. Due to the complexity of the model structure, it is difficult to tune the parameters from a large number of training data.

Stochastic framework, typified by HMMs, are widely used for categorization of human motions. A compact notation $\lambda = \{\Pi, \mathbf{A}, \mathbf{B}\}$ represents an HMM. Π is a set of initial node probabilities $\Pi = \{\pi_i\}$, $\mathbf{A}$ is a transition matrix $\mathbf{A} = \{a_{ij}\}$ whose entries a_{ij} is the probability of transitioning from the i -th node to the j -th node, and $\mathbf{B}$ is a set of output distributions $\mathbf{B} = \{b_i(\theta)\}$. Figure 68.7 shows the overview of the HMM. Human motion is expressed by a sequence of joint angles or link positions, $\mathbf{x} = \{\theta_1, \theta_2, \dots, \theta_T\}$. The parameters of the HMM are optimized by Baum–Welch algorithm, which is one of expectation maximization algorithms, such that the likelihood $P(\mathbf{x}|\lambda)$ of the human motion $\mathbf{x}$ being generated by its relevant HMM λ is maximized [68.30]. The HMM represents spatiotemporal features of the human motions, and is hereafter referred to as motion primitive.

Human motion $\mathbf{x}$ can be classified into a motion category represented by the motion primitive. The classification finds an HMM $\lambda_{\mathcal{R}}$ which is the most likely to

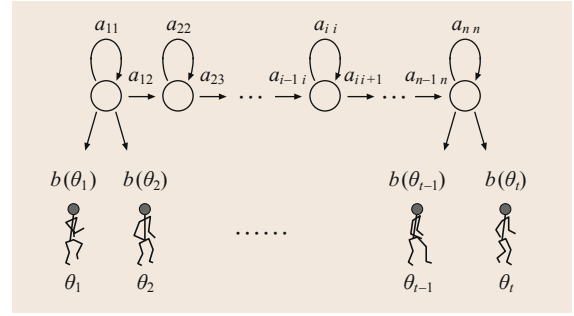


Fig. 68.7 The overview of an HMM. An HMM is the graphical model. A node extracts the spatio feature and an edge extract the temporal feature

generate the human motion as follows

$$\lambda_{\mathcal{R}} = \arg \max_{\lambda} P(\mathbf{x}|\lambda). \quad (68.10)$$

The likelihood $P(\mathbf{x}|\lambda)$ can be efficiently computed in the recursive manner by the forward algorithm

$$\alpha_t(j) = \sum_i \alpha_{t-1}(i) a_{ij} b_j(\theta_t), \quad (68.11)$$

$$P(\mathbf{x}|\lambda) = \sum_i \alpha_T(i), \quad (68.12)$$

where $\alpha_t(j)$ is the probability of generating a sequence $\{\theta_1, \theta_2, \dots, \theta_t\}$ and staying at the j -th node at the time t .

68.3.3 Temporal Sequence of Human Motion

The representations of not only motion segments but also the temporal sequence of them are important for the robots to accurately understand human actions. *Motion graph* is the popular approach to represent the transition between human postures [68.31]. It is possible to transfer between two postures that are similar to one another. This framework creates the edges among the human postures based on their spatial similarities.

The motion segmentation and motion categorization can be extended to the representation of temporal sequence of human motions. Human motion is expressed by a series of motion segments $\{\dots, \mathbf{x}(k-1), \mathbf{x}(k), \mathbf{x}(k+1), \dots\}$ by the segmentation technique, and the series of motion segments is converted to a temporal series of motion primitives $\{\dots, \lambda(k-1), \lambda(k), \lambda(k+1), \dots\}$ by the motion categorization technique. The transition structure of the motion primitives can be extracted by deriving a motion N -gram model from the series of motion primitives. The

motion N -gram model assumes that the motion primitive depends only on its $N-1$ pieces of the motion primitives. The simplest structure is the motion bigram (2-gram) model. The probability of transitioning from the motion λ_i to the motion λ_j can be estimated as

$$P(\lambda_i|\lambda_j) = \frac{\sum_k C[\lambda(k-1) = \lambda_j, \lambda(k) = \lambda_i]}{\sum_k C[\lambda(k) = \lambda_j]}, \quad (68.13)$$

where $C(\lambda)$ is the frequency of the motion λ appearing in the observation of human motions, and this transition probability maximizes the probability of the observation being generated by the motion bigram model.

This transition structure can be used for several applications such as editing animation character, detecting abnormal actions, or predicting human actions [68.32]. In the case of the action prediction, current human motion is classified into the specific motion $\lambda(0)$. The sequence of the motions $\lambda = \{\lambda(1), \lambda(2), \lambda(K)\}$, which is the most likely to be generated by the motion bigram model, can be searched for by Dijkstra's algorithm

$$\begin{aligned} \lambda_p = \arg \max_{\lambda} & P[\lambda(K)|\lambda(K-1)] \\ & \times P[\lambda(K-1)|\lambda(K-2)] \cdots P[\lambda(1)|\lambda(0)]. \end{aligned} \quad (68.14)$$

The selected sequence of motions is considered to be motions predicted from the current motion (VIDEO 764).

68.3.4 Linguistic Interpretation of Human Motion

Integration of the human motions with the natural language leads to not only understanding the human motions in the form of linguistic expressions but also generating robot's motions from the queries of language commands. A framework of RNN with parametric bias has been applied to the integration of the motions and language. One RNN represents the dynamics in the motions, and the other RNN represents the dynamics of language, more specifically sequences of words. The parametric biases shared by these two RNNs join together RNNs [68.33]. Given sentences, the parametric biases for the sentences are estimated in the RNN for the language, the RNN for the motion generates motions using the parametric biases derived from the language RNN. The robot can generate the motions corresponding to the sentences. This conversion from the language to the motions is reversed, and it allows for the conversion from motions to their descriptive sentences [68.34].

Another integration of the human motions with language is stochastic approach. Human action is represented as a sequence of motion primitives $\{\lambda(1), \lambda(2), \dots, \lambda(k)\}$. A sequence of verbs $\omega(1), \omega(2), \dots, \omega(l)$ is also manually assigned to the same human action, where $\omega(i)$ is the verb assigned to the manually segmented motion at the i -th position. The problem of extracting the references between the human motions and the verbs can be considered as a translation problem since the human motion is expressed by a sequence of symbols (Fig. 68.8). The IBM translation model has been widely used in the natural language processing [68.35], and can be applied to integrating the human motions with their relevant verbs [68.36]. This translation model consists of translation probability $t(\lambda|\omega)$ of the motion λ being generated by the verb ω , and alignment probability $a(i|j, l, k)$ that the i -th position in a sequence of the verbs can align to the j -th position in a sequence of the motions. These parameters are optimized such that the following probability that the sequence of verbs generates the sequence of motions is maximized by the expectation-maximization (EM) algorithm.

$$\Phi = P(\lambda(1), \lambda(2), \dots, \lambda(k) | \omega(1), \omega(2), \dots, \omega(l)). \quad (68.15)$$

Additionally, the verb bigram model extracts the transition between two verbs as the verb transition probability $P(\omega_i|\omega_j)$ from the sequences of verbs attached to the human motions. A sequence of verbs $\omega = \{\omega(1), \dots, \omega(l)\}$ which is the most likely to describe the human motion is

$$\omega_R = \arg \max_{\omega} P(\omega|\lambda) = \arg \max_{\omega} P(\lambda|\omega)P(\omega). \quad (68.16)$$

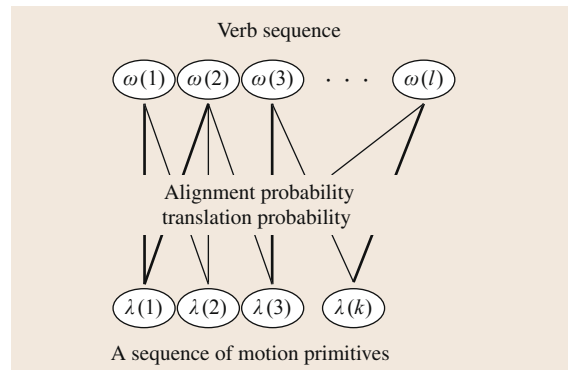


Fig. 68.8 Mapping between sequences of verbs and motion primitives

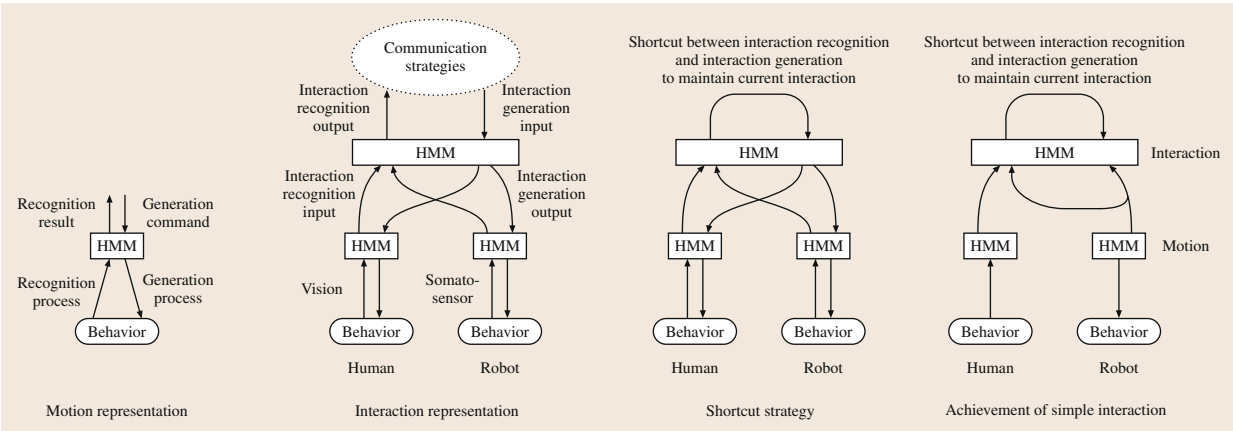


Fig. 68.9 Modeling of the behavioral interaction

$P(\lambda|\omega)$ can be computed using the translation probability and alignment probability, and $P(\omega)$ can be computed using the verb transition probability. The human motion is interpreted as the resultant verb sequence ω_R . This framework has been extended to handling not only verbs but also nouns, adverbs such that human motion can be converted to the descriptive sentences [68.37] (VIDEO 766).

68.3.5 Theory of Communication

HMMs has been extended to hierarchical HMMs (HHMM) or coupled HMMs (CHMM) to represent complicated spatiotemporal features. Statistical model is embedded into each node of the HMM in HHMM while commonly used HMM has an Gaussian distribution function in the node [68.38]. CHMM, in which multiple HMMs interact, is a method for representing mutual dependence between two such as a human and a robot, or a motion and a manipulated object. These approaches may be applied to the interaction that requires the complex representation [68.39]. However, the large number of parameters in these frameworks limits their application, and it is difficult to use these frameworks for human–robot interaction.

One efficient approach to using the representation of human motions as HMM is to design hierarchy for motion primitives and interaction primitives. HMMs representing human whole body motions can be useful to recognize motion observation. The HMMs can be reused to generate human-like motions for humanoid robot. A node is sampled according to the node transition probabilities, and a configuration is sampled according to the output probabilities on the selected node. The generation of the robot motion by the sampling manner can be done in the same framework. It is fundamental for the humanoid robot not only to rec-

ognize human motions but also to generate human-like motions, and this framework has been applied to the interaction between a human and a humanoid robot as shown in Fig. 68.9.

The behavioral interaction is defined by the exchange of the motion primitives between the two [68.37]. Observation of two interacting humans is converted to a sequence of pairs of motion primitives by recognizing their motions using the HMMs. HMMs in the higher level represent these interactions. These HMMs are more abstract analogy of representation of the motions, and useful for recognition and generation of the interaction patterns. A hypothesis is then introduced for the simple commutation, more specifically the communication is established by recognizing the relationship of the two and subsequently maintaining it.

The two recognition output of the human and robot using the HMMs in the lower level becomes the input

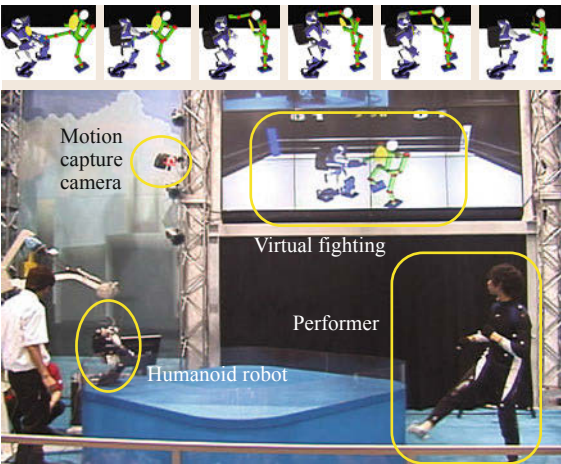


Fig. 68.10 Human–robot interaction realized by a symbolical hierarchical communication model

of the HMMs in the higher level, and the interaction can be recognized as a higher HMM. The current node can also be estimated in the selected higher HMM. The generation output from this node are a pair of two motion primitives for the human and robot, and they become the input of the lower HMMs. One motion primitive for the human becomes the prediction of human behavior, and another motion primitive for the robot becomes the command for the motion generation. The recognition and generation by the higher HMMs imply the

estimated state of the interaction and the control strategy for the interaction, respectively. The importance for the naturally drifting interaction is to represent the process of the control strategy based on the estimated interaction state as a shortcut between the recognition and generation [68.40]. The experiment of interaction between the human and robot in a virtual world demonstrated its validity as shown in Fig. 68.10, and is further applied to the human–robot interaction with compliant physical contacts [68.41].

68.4 Reconstruction for Robots

This section reviews some examples of synthesizing human-like motions of robots or virtual humans based on human motions and/or physiological model.

68.4.1 Reconstruction for Virtual Humans

Instead of using inverse kinematics as described in Sect. 68.2.2, Demerican et al. [68.42] developed a method for reconstructing human motions by directly tracking marker trajectories with a physically simulated skeleton model. Figure 68.11 shows the set of markers tracked as well as the skeleton model used in the simulation. Examples of measured and simulated marker trajectories are shown in Fig. 68.12, which demonstrates the smoothness of the reconstructed human motions.

68.4.2 Controller Optimization from Physiological Model

Recorded human motion is an outcome of the human motor control. Instead of using the outcome, i. e., the

motion, Wang et al. [68.44] optimized controllers based on physiological human model that includes eight major leg muscles, including both uniarticular (drive single joint) and biarticular (drive two joints) (Fig. 68.13). The method optimizes the controller parameters based on simulation considering the physiological muscle properties [68.9]. The results demonstrate good match with human measurements in terms of both joint trajectories and torques.

68.4.3 Reconstruction for Physical Robots

Tracking human motions with a physical humanoid robot is not as straightforward as it may appear even if the robot has human-like body topology, due to various differences between the human and robot bodies.

First, there is always some difference in the kinematic properties such as dimensions and proportion. In manipulation, for example, simply copying the joint angles will not result in the same hand positions if the upper and lower arm lengths are different.

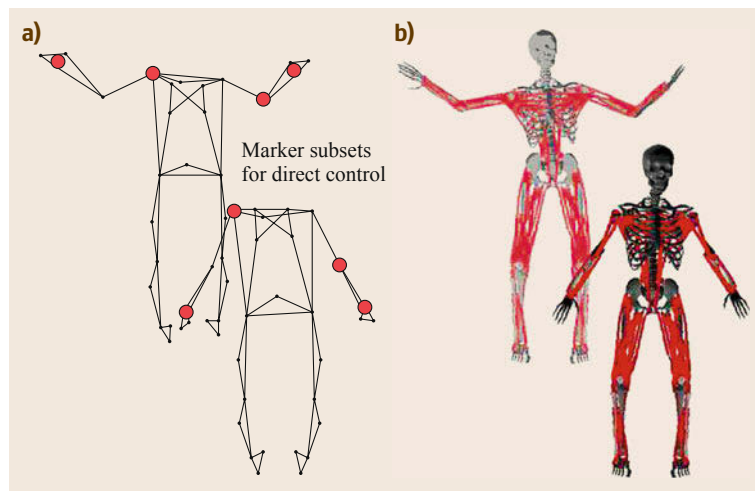


Fig. 68.11a,b Marker set and skeletal model used in (after [68.42]).
(a) Motion capture data. (b) Skeleton model in simulation and active interfaces (SAI) (after [68.43])

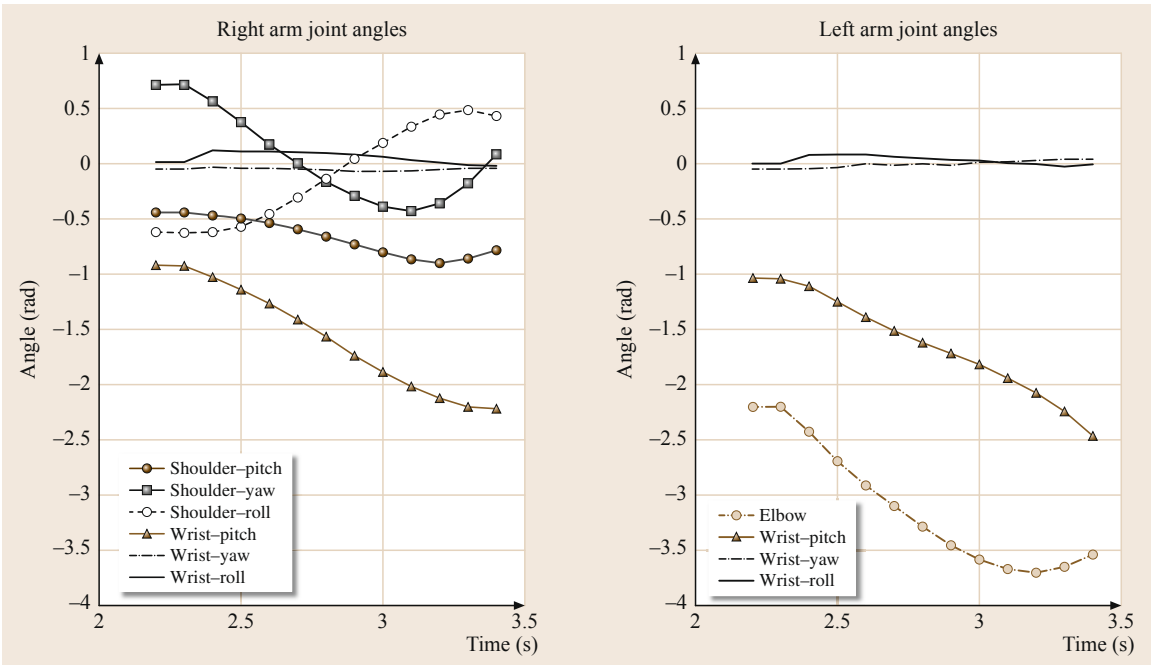


Fig.68.12a,b Joint angles computed from direct marker tracking (after [68.42]). (a) Right arm joint angles. (b) Left arm joint angles

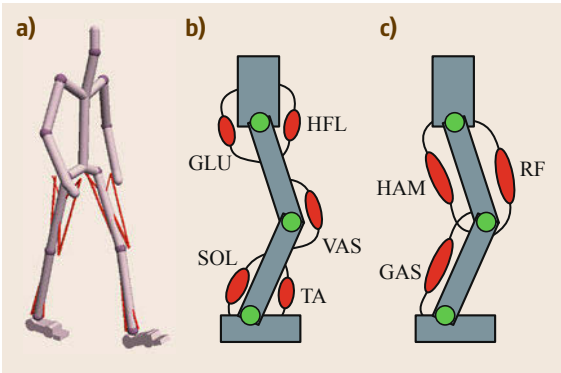


Fig.68.13a–c The musculoskeletal model used in [68.44] (a) skeleton and muscles (red lines), (b) five uniarticular muscles, and (c) three biarticular muscles

The kinematic difference comes not only from different dimensions, but also from flexibility of the human body that is difficult to replicate with mechanical systems. For example, the human spine has much more degrees of freedom than the torso of typical humanoid robots.

Secondly, robot hardware is generally much more restrictive in terms of joint motion range as well as velocity, acceleration, and torque limits. As a result,

robots cannot always perform the same range of motion as humans. We would therefore have to modify the original motions such that they are within the hardware limits.

Finally, the inertial properties such as mass, inertia, and center of mass locations are different. In motions that involve balancing, the different inertial properties may make the motion unbalanced and cause a fall.

While motion capture data have been frequently applied to virtual human characters in simulated environments [68.45–47], much less work has been done on directly controlling humanoid robots with human motion capture data. *Nakaoka et al.* [68.2] divided captured dancing motion into multiple tasks and optimized each task to be feasible for the robot dynamics. *Miura et al.* [68.48] computed feasible center of mass trajectory based on the center of pressure trajectory determined from the footsteps in the motion data, and then computed the joint motions by inverse kinematics.

Ott et al. [68.49] and *Yamane and Hodgins* [68.50, 51], on the other hand, combined online balance control and tracking control to address the problem of different dynamics. Figure 68.14 depicts some snapshots from the hardware experiment of tracking a human motion capture sequence with a floating-base humanoid robot [68.51] ([VIDEO 765](#)).

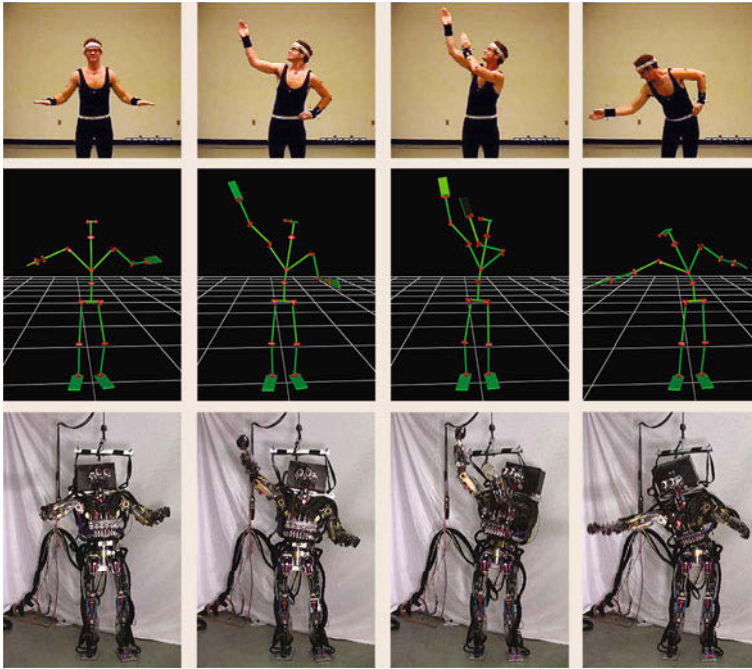


Fig. 68.14 Snapshots from the hardware experiment

Video-References

-  **VIDEO 762** Example of optical motion capture data converted to joint angle data available from <http://handbookofrobotics.org/view-chapter/65/videodetails/762>
-  **VIDEO 763** Example of muscle tensions computed from motion capture data available from <http://handbookofrobotics.org/view-chapter/65/videodetails/763>
-  **VIDEO 764** The Crystal Ball: Predicting future motions available from <http://handbookofrobotics.org/view-chapter/65/videodetails/764>
-  **VIDEO 765** Human motion mapped to a humanoid robot available from <http://handbookofrobotics.org/view-chapter/65/videodetails/765>
-  **VIDEO 766** Converting human motion to sentences available from <http://handbookofrobotics.org/view-chapter/65/videodetails/766>

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69. Physical Human–Robot Interaction

Sami Haddadin, Elizabeth Croft

Over the last two decades, the foundations for physical human–robot interaction (pHRI) have evolved from successful developments in mechatronics, control, and planning, leading toward safer lightweight robot designs and interaction control schemes that advance beyond the current capacities of existing high-payload and high-precision position-controlled industrial robots. Based on their ability to sense physical interaction, render compliant behavior along the robot structure, plan motions that respect human preferences, and generate interaction plans for collaboration and coaction with humans, these novel robots have opened up novel and unforeseen application domains, and have advanced the field of human safety in robotics.

This chapter gives an overview on the state of the art in pHRI. First, the advances in human safety are outlined, addressing topics in human injury analysis in robotics and safety standards for pHRI. Then, the foundations of human-friendly robot design, including the development of lightweight and intrinsically flexible force/torque-controlled machines together with the required perception abilities for interaction are introduced. Subsequently, motion-planning techniques for human environments, including the domains of biomechanically safe, risk-metric-based, human-aware planning are covered. Finally, the rather recent problem of interaction planning is summarized, including the issues of collaborative action planning, the definition of the interaction planning problem, and an introduction to robot reflexes and reactive control architecture for pHRI.

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69.1 Classification

Robotics is currently undergoing a fundamental paradigm shift, both in research and real-world applications. Classically, it was dominated for the last decades by possibly dangerous position-controlled rigid robots carrying out typical automation tasks, such as positioning and path tracking in various applications. Recently, a new generation of mechatronic robots has appeared on the landscape, including novel concepts in general robot design within the soft-robotics context. This trend brings us closer to the long-term goal of safe, seamless physical human–robot interaction (pHRI) in the real domestic and professional world (Fig. 69.1).

Recent advances in physical human–robot interaction have shown the potential and feasibility of robot systems for active and safe workspace sharing and collaboration with humans. The fundamental breakthrough was the human-centered design of robot mechanics and control (soft-robotics), which also induced the novel research stream of intrinsically elastic robots (series elastic actuators (SEA) or its generalization variable impedance actuators (VIA)). By considering the physical contact of the human and the robot in the design phase, possible injuries due to unintentional contacts can be considerably mitigated. Furthermore, taking into account the human's intention and preferences will en-

able the realization of human-friendly motions and interaction behavior. Some of the most advanced systems that were developed are now entering into industrial markets. These technologies serve both industrial and service-oriented domains. Possible future applications of these novel devices developed for close interaction with humans are depicted in Fig. 69.2. They range from industrial coworkers and mobile servants over robots in the professional service sector, assistive devices for physically challenged individuals, to service robots for the support of general household activities. All of these applications share the common requirement of close, safe, and dependable physical interaction between human and robot in a shared workspace. Therefore, such robots need to be carefully designed for human friendliness. That is, they have to be able to safely sense, reason, learn, and act in a partially unknown world inhabited by humans. In turn, this set of requirements necessitates the design of novel solutions in various theoretical and technological developments. In contrast to the classical modular view on robotics technology, and the role humans play in this, a fundamental paradigm shift in robot development has to be pursued. While encompassing safety issues based on biomechanical human injury analysis as well as on the kinesiological biomechanics



Fig. 69.1 The current paradigm shift in robotics induced by new target domains and robots toward the vision of close human–robot coexistence (courtesy of Keller und Knappich Augsburg (KUKA), Deutsches Zentrum für Luft- und Raumfahrt (DLR), ABB, Rethink Robotics)

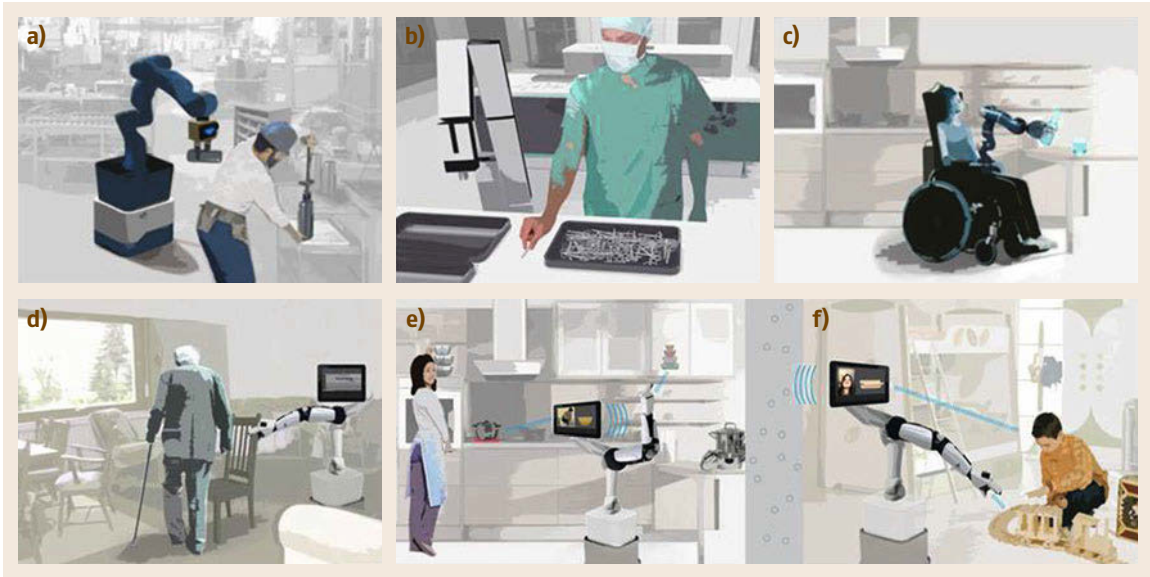


Fig. 69.2a–f Application examples for pHRI, ranging from shop floor logistics and manipulation (a,b), over professional service robots and assistive devices for the disabled (c,d), to service robots in domestic applications (e,f)

of human movements, human-friendly hardware design and interaction control strategies, learning, perceptive, and cognitive key components have to be developed and validated. These need to enable robots to track, understand, and predict human motions in real time in a weakly structured dynamic environment. Apart from developing the capabilities for interactive autonomy including self-improvement, human safety and physical interaction have to be embedded at the cognitive decisional level as well. This will enable the robots to react or physically interact with humans in a safe and autonomous way. Biomechanical knowledge, neuromechanical insights, and biologically motivated variable compliance actuators can be used to design manipulation/interaction systems of varying complexity close to human properties and performance. Further fundamental insights into novel designs of VIAs for an improved torque/mass ratio and energy efficiency with new control methods to exploit the stiffness and damping properties are required.

Planning and adapting motions and tasks of such complex systems in real-time require new concepts, including tight coupling of control, planning, and learning, which will lead to reactive behaviors capable of self-improvement. Moreover, self-explaining interaction and communication frameworks need to be developed to enhance the system usability and interpretability for humans. These should, for example, communicate whether a situation is safe or dangerous using not only verbal, but also nonverbal communi-

cation cues, such as gestures and emotional feedback. Finally, the dependability of all system components and algorithms is a major issue, the systematic treatment of which is of particular importance for subsequent industrial commercialization of the technology and also for the commercial domestic use of robots in everyday environments. Thus, the foreseeable breakthrough of the next generation of robotic systems in flexible automation in both small and medium enterprises (SMEs) and global market companies depends primarily on the pHRI development over the next years. Robotic assistance in manual processes that advantageously partner human and robot workers has an enormous unexplored potential to amplify productively in processes that previously could not be automated due to technological, cost, or efficiency reasons. Furthermore, very promising application domains of the technology are in the professional service sector (e.g., hospital support systems) and in the logistics domain (food logistics and quality inspection), which are so far to a large extent still purely manual work places. As the natural next step, systems capable of pHRI will enter the home sector as home assistants, elderly care assist, and assistive devices ([VIDEO 607](#), [VIDEO 614](#), [VIDEO 618](#), [VIDEO 623](#)) for physically challenged people ([VIDEO 618](#), [VIDEO 619](#), [VIDEO 620](#), [VIDEO 621](#), [VIDEO 622](#)). First, rather basic tasks, such as fetch-and-carry or environment manipulation, will be solved followed by applications with increasing complexity.

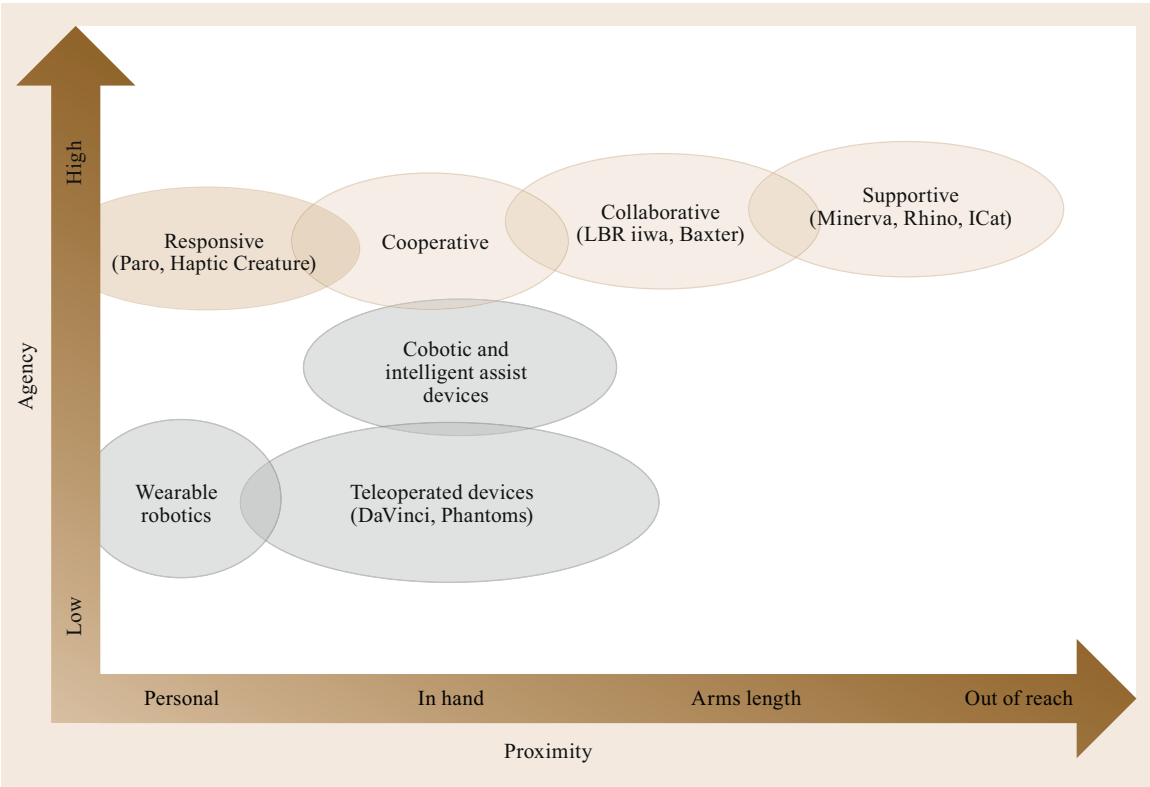


Fig. 69.3 Classification scheme for pHRI, by proximity of the interaction and agency (available autonomy) of the robot

69.1.1 Classification of Interaction

pHRI falls into the category of *proximate* interaction where humans and robots are colocated, as opposed to *remote* or teleoperated interaction (Chap. 43) [69.1]. Beyond proximity, the nature of the physical interaction can be understood in the context of the tasks and roles undertaken by the robot and human actors in a pHRI scenario. In all of these scenarios, a key feature is the available autonomy, or agency, of the robot partner for performing its portion of the task. This agency separates pHRI from Cobotic devices [69.2] and other passive robotic lift assists that require, by design, input from the operator.

Most work in pHRI can be generally classified across three broad categories of interaction: *supportive*, *collaborative*, and *cooperative*. Ordered in this way we note that these interactions are marked by increasing frequency and necessity of physical contact with the robot and level of proximity to the user (Fig. 69.3). Further categories include touch-based, personally responsive robots, for example, Paro [69.3] and the Haptic Creature [69.4], and wearable robots (Chap. 70).

In *supportive* interactions, we group interactions where the robot is not integral to the central performance of a task, but instead provides the human with the tools, materials, and information to optimize the human’s task performance or objectives, for example, museum tour guide robots, shopping assistant robots for aiding seniors [69.5], and homecare robots (Chaps. 65 and 73). In this context, pHRI is typically concerned with safety, that is, preventing and mitigating the effect of unexpected contacts or collisions, and performing appropriate proxemic behavior. When required, physical interaction is infrequent and transitory in nature – typically limited to handoffs or other infrequent transactional exchanges. To support safety, as well as these limited physical interactions, well-structured human–robot communication (Chap. 71) is essential. For example, recent work [69.6–11] has demonstrated the importance of bi-lateral gesture cues in performing turn-taking, information sharing, close proximity activities, and precontact handover operations.

In *collaborative* interactions (VIDEO 609), the human and robot both work on the task, with the labor divided between the robot and human, each separately completing the parts of the task best suited to their

abilities, but more frequently interacting through turn-taking and part/tool passing [69.12, 13] (👁 VIDEO 716), or haptically enabled mode switching where contact is used to switch the robot's interactive behavior [69.14] (👁 VIDEO 717, 👁 VIDEO 632). In these scenarios, the human completes task elements requiring human dexterity or decision making, while the robot completes elements not well suited to direct human involvement, for example, repetitive or high-force applications, chemical deposition, or precision placement. In both supportive and collaborative interactions, physical space is often shared but planned physical interactions, although much more frequent, are still *transactional* in nature.

Cooperative interactions refer to the extension of cooperative manipulation (see also Chaps. 39 and 70) to include force interactions with humans. This type of interaction is differentiated from Cobots in that the robot operates as an independent agent, rather than a passive assist. That is, the human and the robot work in direct physical contact, or indirect contact through a common object, with continuous and cooperative shared control of the task. Cooperative interactions encompass tasks, such as cooperative lifting and carrying [69.15–17] (👁 VIDEO 613, 👁 VIDEO 820), kinesthetic teaching [69.18] (👁 VIDEO 627), coordinated material handling (e.g., managing long and flexible objects), and rehabilitation therapy (Chap. 64).

69.2 Human Safety

Providing safety in **pHRI** is a multifaceted challenge and requires an analysis on various levels of abstraction. **pHRI** aims at the coexistence of humans and robots in a common workspace and at extending their communication modes by physical means. This spatial proximity leads to a variety of *potential threats*, determined by the current state of the system of interest, which consists of the human(s), the robot(s), and their surrounding environment. Understanding the respective threats, in particular regarding potential human injury originating from physical robot–human contacts, and embedding the insights accordingly into safety standards/regulations is one of the major challenges of

nowadays robotics (note that this chapter does not cover functional safety or robot dependability).

69.2.1 Human Injury in Robotics

Impact Scenarios

In order to quantify human injury that may occur in the context of **pHRI**, one needs to understand how mechanical contacts may cause injury in principle. Figure 69.4 depicts relevant robot–human impact scenarios. These may involve unconstrained impacts, clamping in the robot structure, constrained impacts, partially constrained impacts, and resulting secondary

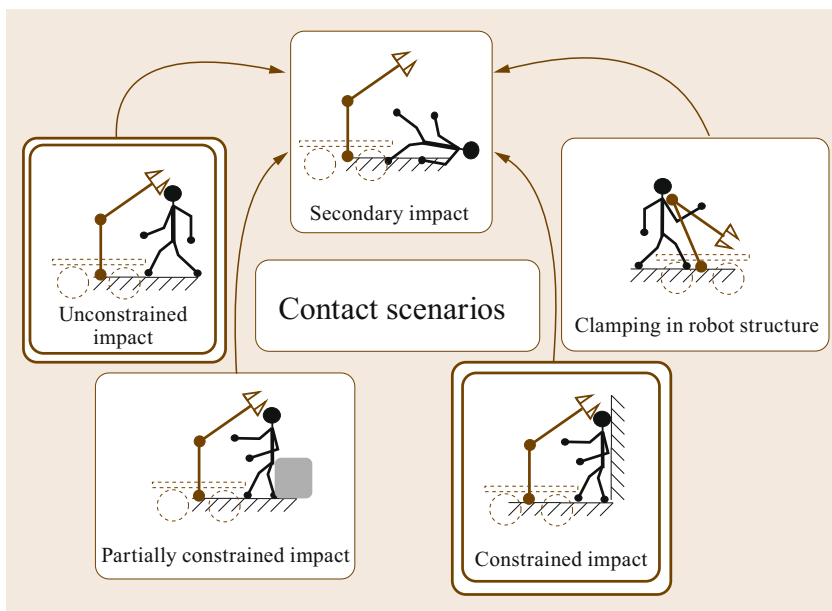


Fig. 69.4 Robot–human impact scenario classes. Unconstrained and constrained impacts are considered the two main scenarios

impacts [69.19]. Apart from such situational definitions, the most urgent question is how to quantify the human injury level that might occur due to a collision between human and robot. The understanding of human injury has been treated in the fields of injury biomechanics and forensics for several decades and the respective studies served for the early work on human injury in robotics. In fact, various injury measures from biomechanics and forensics were applied to human injury analysis in robotics [69.19–25]. An overview on the most important existing injury classification metrics and biomechanical injury measures can be found in [69.26] (VIDEO 608). The most important results from the biomechanics, forensics, and robotics literature are briefly reviewed now.

Overview Biomechanics Literature

In order to derive the injury characteristics of different body parts for direct collisions with an impactor, which is the most relevant case for robotics, countless experiments and publications have been produced over the last

50 years. The investigated impactors used in robotics and biomechanics experiments vary significantly in size and shape. However, from the test setups, one can identify and cluster principal geometric primitives. The main primitives and their parameters are depicted in Fig. 69.5. The z -axis of the coordinate frame associated with each primitive defines the direction of impact u .

Numerous relevant impact experiments with cadavers, volunteers, crash test dummies, and biological tissue for the head, neck, and chest were generated (Tables 69.1–69.4). There for all selected experimental campaigns, the collision scenario, impacted body part, impact parameters according to Fig. 69.5, subject, and impact velocity are listed. For describing the collision scenario, we use the following abbreviations: D: dynamic, QS: quasi-static, U: unconstrained, C: constrained, PC: partially constrained. A collision experiment denoted by **DU** is, thus, dynamic unconstrained, while quasi-static constrained impacts are labeled **QSC** (Sect. 69.2.1, *Synopsis*). The respective impactor type and parameters are listed for comparison.

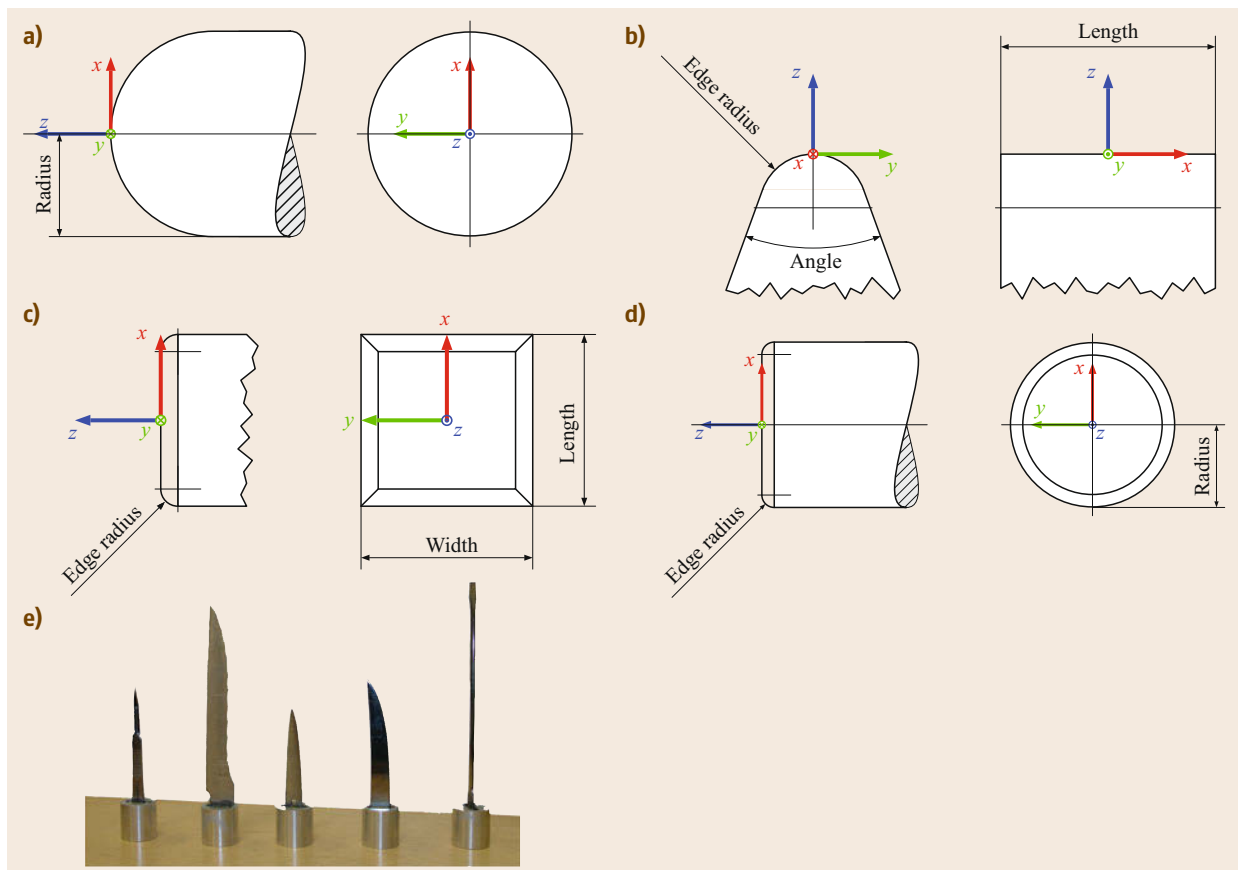


Fig. 69.5a–e Typical impactor primitives with according parameters. (a) Sphere, (b) edge, (c) cuboid, (d) flat circular, (e) sharp tools

Table 69.1 Overview of selected impact experiments from biomechanics and robotics literature. Body part: Head

Impactor type	Impactor parameters	Collision case	Subject	Mass (kg)	Velocity (m/s)	References
Flat circular						
Maxilla, zygoma, frontal, temporo-parietal, mandible	14.3 mm radius	dynamic constrained (DC)	Cadaver	1.08–3.82	2.99–5.97	[69.27, 28]
Temporo-Parietal	12.7 mm radius	DC	Cadaver	10.6	2.7	[69.29]
Nose	14.3 mm radius	DC	Cadaver	3.2	1.56–3.16	[69.30]
Frontal	35 mm radius	DU	Cadaver	14.3	3.37–6.99	[69.31]
Edge						
Nose	12.5 mm radius	DU	Cadaver	32, 64	2.77–6.83	[69.32]
Maxilla, zygoma, frontal	10 mm radius	DC	Cadaver	14.5	2.4–4.2	[69.33]
Frontal	12.7 mm radius	dynamic partially constrained (DPC)	Cadaver	∞ (human falling on impactor)	2.23–3.14	[69.34]
Cuboid						
Temporo-parietal	50 mm length, 100 mm width	DC	Cadaver	12	4.3	[69.29]
Frontal	Size not specified, padded	DPC	Cadaver	5.31–5.97	3.56–9.6	[69.35]
Frontal	size not specified	DPC	Cadaver	∞ (human falling on impactor)	2.23–3.87	[69.34]
Sphere						
Frontal	120 mm radius	DU, QSC, DPC	Hybrid III dummy	4, 67, 1980	0.2–4.2	[69.36, 37]
Frontal	203.2, 76.2 mm radius	DPC	Cadaver	∞ (human falling on impactor)	2.87–3.5	[69.34]

Table 69.2 Overview of selected impact experiments from biomechanics and robotics literature. Body part: Torso

Impactor type	Impactor parameters	Collision case	Subject	Mass (kg)	Velocity (m/s)	References
Flat circular						
Thorax	76.2 mm radius, 12.77 mm edge radius	DU, DC	Cadaver	1.6–23.6	4.34–14.5	[69.38, 39]
Thorax	76 mm radius, rubber padded	DU	Volunteer	10	2.4–4.6	[69.40]
Thorax	76.2 mm radius, 12.77 mm edge radius	DU	Cadaver	19.27	4.0–10.6	[69.41]
Abdomen	12.7 mm radius	DU	Cadaver	32, 64	4.9–13.0	[69.42]
Sphere						
Thorax	120 mm radius	DU, QSC	Hybrid III dummy	4, 67, 1980	0.2–4.2	[69.36, 37]
Abdomen	5, 12.5 mm radius	DC	Pig tissue	2–10	0.5–4.0	[69.25]
Edge						
Abdomen	45° angle, 200 mm length, 0.2 mm edge radius	DC	Pig tissue	2–10	0.5–4.0	[69.25]

Table 69.3 Overview of selected impact experiments from biomechanics and robotics literature. Body part: Upper extremities

Impactor type	Impactor parameters	Collision case	Subject	Mass (kg)	Velocity (m/s)	References
Edge						
Forearm	12.5 mm radius, angle 0°	DC	Cadaver	9.48	3.63	[69.43]
Forearm	size not specified	DC	Cadaver	9.75	2.44, 4.23	[69.44]
Shoulder, upper arm, forearm	5 mm edge radius, 30° angle	DC	Volunteer	4.16, 8.65	0.45–1.25	
Flat circular						
Forearm, hand	size not specified	QSC	Cadaver	∞ (velocity control)	25 mm/min	[69.45]

Table 69.4 Overview of selected impact experiments from biomechanics and robotics literature. Body part: Lower extremities

Impactor type	Impactor parameters	Collision case	Subject	Mass (kg)	Velocity (m/s)	References
Sharp	Fig. 69.5	DC	Pig tissue, volunteer	4	0.16–0.8	[69.24]

Next, some essential characteristics of human–robot impacts are elaborated for a more general understanding of the underlying dynamics.

Robot–Human Impacts

Let us assume that of a serial chain rigid robot consisting of n joints, there is at most a single link involved in a collision. Let

$$\dot{\mathbf{x}}_c = \begin{pmatrix} \mathbf{v}_c \\ \boldsymbol{\omega}_c \end{pmatrix} = \begin{pmatrix} \mathbf{J}_{c,\text{lin}}(\mathbf{q}) \\ \mathbf{J}_{c,\text{ang}}(\mathbf{q}) \end{pmatrix} \dot{\mathbf{q}} = \mathbf{J}_c(\mathbf{q}) \dot{\mathbf{q}} \in \mathbb{R}^6 \quad (69.1)$$

be the stacked (screw) vector of linear velocity at the contact point and the angular velocity of the associated robot link, with an associated (geometric) contact Jacobian $\mathbf{J}_c(\mathbf{q})$ that is a function of the joint angle $\mathbf{q}$. Accordingly, the Cartesian collision wrench is denoted by

$$\mathcal{F}_{\text{ext}} = \begin{pmatrix} \mathbf{f}_{\text{ext}} \\ \mathbf{m}_{\text{ext}} \end{pmatrix} \in \mathbb{R}^6. \quad (69.2)$$

Robot Collision Modeling. When such a collision occurs, the robot dynamics becomes

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) + \boldsymbol{\tau}_F = \boldsymbol{\tau} + \boldsymbol{\tau}_{\text{ext}}, \quad (69.3)$$

where $\mathbf{M}(\mathbf{q}) \in \mathbb{R}^{n \times n}$ is the symmetric and positive definite joint space inertia matrix, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} \in \mathbb{R}^n$ is the centripetal and Coriolis vector, and $\mathbf{g}(\mathbf{q}) \in \mathbb{R}^n$ is the gravity vector; $\boldsymbol{\tau} \in \mathbb{R}^n$ is the motor torque, and $\boldsymbol{\tau}_F \in \mathbb{R}^n$ is the dissipative friction torque; $\boldsymbol{\tau}_{\text{ext}} \in \mathbb{R}^n$ is the typically unknown external joint torque given by

$$\boldsymbol{\tau}_{\text{ext}} = \mathbf{J}_c^T(\mathbf{q}) \mathcal{F}_{\text{ext}}. \quad (69.4)$$

The effective mass m_u of a robot acting in the instantaneous collision direction $\mathbf{u}$, which has to be consistent to $\mathbf{J}_c(\mathbf{q})$, can be deduced from $\mathbf{M}(\mathbf{q})$ via the Cartesian kinetic energy matrix $\boldsymbol{\Lambda}(\mathbf{q})$. This is defined as

$$\boldsymbol{\Lambda}(\mathbf{q}) = [\mathbf{J}_c(\mathbf{q})\mathbf{M}(\mathbf{q})^{-1}\mathbf{J}_c(\mathbf{q})^T]^{-1}, \quad (69.5)$$

where the inverse of $\boldsymbol{\Lambda}(\mathbf{q})$ is based on the decomposition of the kinetic energy matrix

$$\boldsymbol{\Lambda}(\mathbf{q})^{-1} = \begin{bmatrix} \boldsymbol{\Lambda}_v(\mathbf{q})^{-1} & \bar{\boldsymbol{\Lambda}}_{v\omega}(\mathbf{q}) \\ \bar{\boldsymbol{\Lambda}}_{v\omega}(\mathbf{q})^T & \boldsymbol{\Lambda}_\omega(\mathbf{q})^{-1} \end{bmatrix}, \quad (69.6)$$

with $\bar{\boldsymbol{\Lambda}}_{v\omega}(\mathbf{q}) = \mathbf{J}_{c,\text{lin}}(\mathbf{q})\mathbf{M}(\mathbf{q})^{-1}\mathbf{J}_{c,\text{ang}}(\mathbf{q})^T$. Finally, m_u is found to be

$$m_u = [\mathbf{u}^T \boldsymbol{\Lambda}_v(\mathbf{q})^{-1} \mathbf{u}]^{-1}. \quad (69.7)$$

It should be noted that the Jacobian has to be the *center-of-mass-Jacobian*. Otherwise, the entire inverse of the Cartesian inertia tensor has to be used, and not just its translational component block. More details can be found in [69.46]. We assume the local impact curvature in the $\mathbf{u}$ -direction to be denoted by c_u .

Characteristic Robot–Human Impact Force Profile.

A physical collision between robot and human is typically characterized by a distinct force profile that is composed by two consecutive phases (note that for unconstrained soft-tissue collisions these two phases can simplify into a single *Phase I* impact) (Fig. 69.6):

1. Phase I is characterized by a very short impact, governed by the robot- and human-reflected dynamics.
2. Phase II is characterized by a quasistatic contact event. Without clamping, this is a pushing force, whereas if the human is clamped it is a crushing force.

Phase I can be treated from a pure impact physics, almost open-loop point of view, that is, it is determined by the reflected inertia, velocity, and impact curvature c_u of the robot together with the characteristics of the respective body part that is being struck. The maximum contact force is denoted F_I .

Phase II, on the other hand, has to be further subdivided into either *clamping* or *no clamping* incident. In the case of no clamping, the maximum force is F_{IIA} , whereas for clamping, the maximum force is F_{IIB} . In particular, *Phase II* is highly robot control and design dependent and is especially important in the case of clamping:

- *Phase IIA: No clamping.* Typically, for free impacts at robot velocities > 0.3 m/s, F_{IIA} is significantly smaller than F_I . Otherwise, F_I is smaller than F_{IIA} and is governed by the robot actuator torques (active quasistatic pushing) and the reaction of the human body that is mainly governed by its reflected impedance.
- *Phase IIB: Clamping.* In the case of clamping, the final maximum force F_{IIB} is limited by the maximum motor torques $\boldsymbol{\tau}_{\text{max}}$ of the robot via $\mathcal{F}_{\text{ext}} = \mathbf{J}_c^{T\#} \boldsymbol{\tau}_{\text{max}}$, where $\mathbf{J}_c^{T\#}$ is the contact Jacobian pseudoinverse. If the robot is powerful enough to generate active contact forces that penetrate or break human tissue/structure, the contact force is, of course,

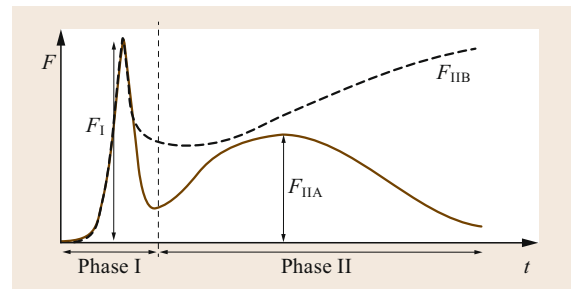


Fig. 69.6 Typical robot–human collision force profiles

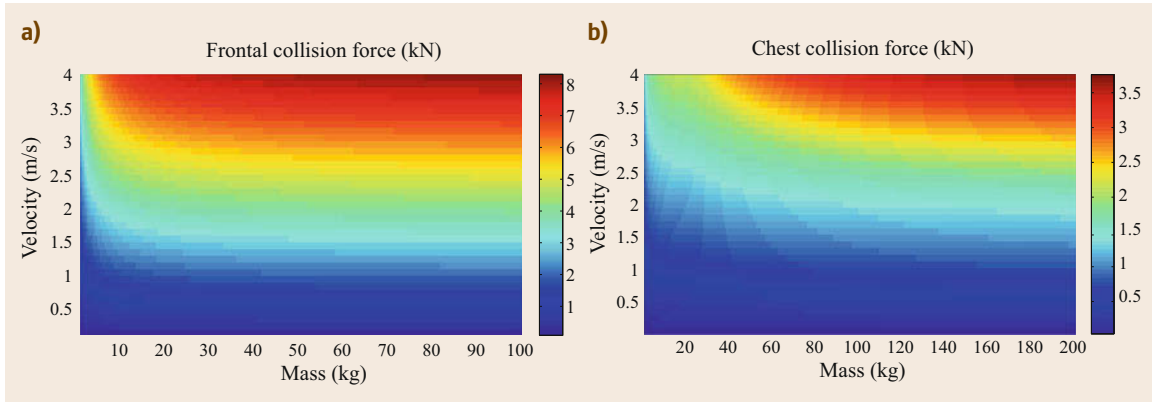


Fig. 69.7a,b Mass–velocity dependency for (a) human head and (b) chest contact force. A mass–spring–mass model is used for collisions against the head, where the head mass M_H is 4.5 kg and the approximate contact stiffness of the frontal bone $K_H = 1000 \text{ N/mm}$ (after [69.33]). For the chest, the model proposed in [69.47] is used

limited by the human maximum tissue resistance. Please note that singularities need careful treatment, which, however, goes beyond the scope of the chapter.

Next, the influence of robot mass and velocity for the unconstrained impact are described. This analysis is particularly important to understand Phase I.

Influence of Robot Mass and Velocity. Assume a simple mass–spring–mass model for the impact between human and robot. M_H is the reflected inertia of the human. K_H is the contact stiffness, which is in the case of a rigid robot mainly the effective stiffness of the human contact area. $\dot{x}_{re}^0$ is the relative impact velocity between the robot and human. Solving the corresponding differential equation leads to the maximum contact force

$$\mathcal{F}_{ext}^{\max} = \sqrt{\frac{m_u M_H}{m_u + M_H}} \sqrt{K_H \dot{x}_{re}^0}. \quad (69.8)$$

Assume a simplifying decoupling of the head from the torso, which holds for the short duration of the impact. For the post-impact phase, neck stiffness and body inertia have to be considered, which complicates the analysis considerably. The dependency of frontal bone contact force on the robot mass and velocity is depicted in Fig. 69.7a. It can be observed that collision force (which is a well-known bone fracture indicator) generally increases with velocity. For increasing mass, however, a saturation effect takes place. After a certain robot mass has been reached ($m_u \approx 20 \text{ kg}$ in Fig. 69.7), additional weight has only negligible influence on collision force. This inertial saturation effect can also be observed for

other impact locations, such as contacts with the chest (Fig. 69.7b).

If the robot mass is significantly larger than the human head mass, that is, $m_u \gg M_H$, (69.8) reduces to

$$\mathcal{F}_{ext}^{\max}(m_u \gg M_H) = \sqrt{K_H M_H} \dot{x}_{re}^0. \quad (69.9)$$

This shows that for a robot with significantly larger reflected inertia than the human head, only the contact stiffness, the impact velocity, and the mass of the human head are relevant but not the robot mass.

The behavior of human tissue during collisions is complex. Consequently, surrogates cannot reveal the entire diversity. Accordingly, the conduction of human voluntary experiments is necessary to fully understand human injury and pain dynamics in robotics.

Human–Robot Impact Voluntary Testing

The following experimental test was the first systematic analysis in this direction. The voluntary experiments were conducted with a healthy young adult in the year 2011. The collision experiments were performed with the KUKA/DLR lightweight robot (LWR) and the following approaches to injury and pain analysis were carried out: *injury severity analysis according to AO* (Arbeitsgemeinschaft für Osteosynthesefragen), *biomechanical analysis, pain, and imaging methods*. The setup and experiment steps are depicted in Fig. 69.8. The robotic system allows to conduct controlled robot–human collisions in order to analyze input parameters and their effect on output parameters, such as pain and injury. Measured impact characteristics and quantities included impact force, impact area, tissue displacement, tissue stiffness, stress, impact velocity, kinetic energy, and energy density. The reflected inertia

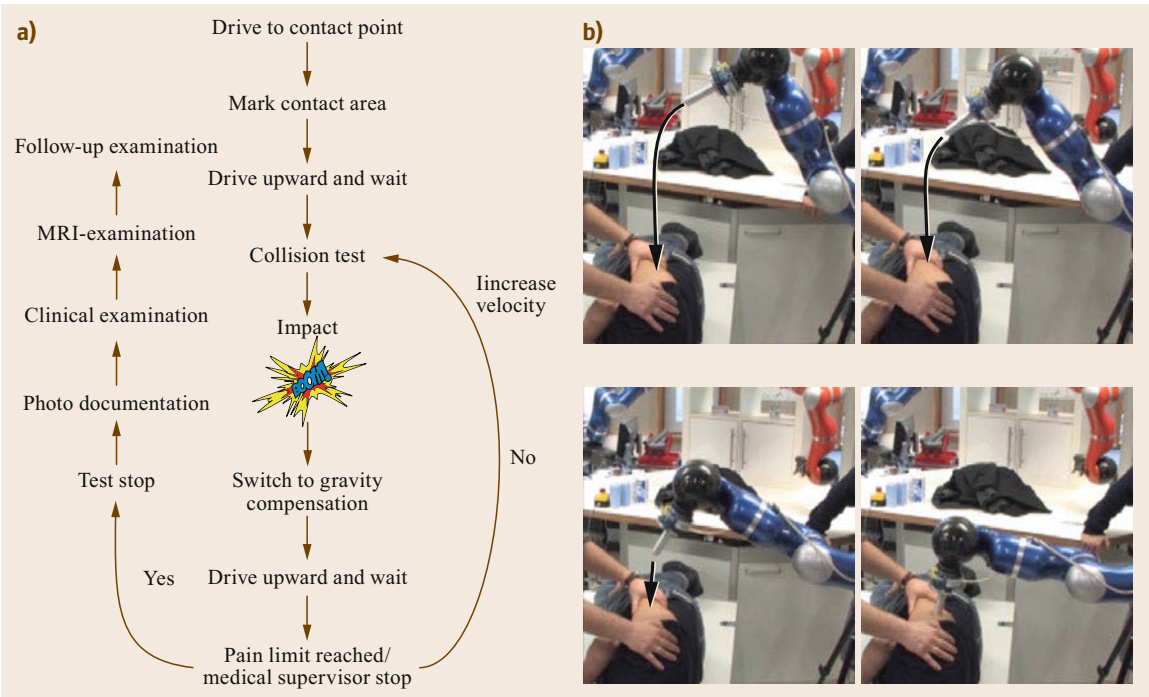


Fig. 69.8 (a) Flow chart depicting the basic experimental steps. (b) Collision trajectory with subject

was kept constant at $m_u = 3.75$ kg for every test. The used impactor for the resulting Table 69.5 was a sphere with a radius of 12.5 mm.

The injury was defined using the AO-classification [69.48] directly after each test series. Each impact series was carried out at the same location on the human body at increasing impact velocity until the participant initiated a controlled system stop during the experiment. The impact areas were then imaged with a magnetic resonance imaging (MRI) after a time interval of about 4–5 h. The remaining tissue did not show any pathological signs. Compared to an equivalent drop test in [69.25] with abdominal pig tissue (large sphere, 4.2 kg, 2.5 m/s), the voluntary experiments provide similar results in terms of injury severity. The maximum velocity of 2.55 m/s is at the border of inducing a contusion. Where there were no marks immediately after impact, a mild contusion formed at day 1. For the pain tolerance at a visual analog scale (VAS) of 6/10, an impact force of $F = 272.2$ N was measured. The energy density appears to have the most significant correlation to pain.

Synopsis

An overview of the potential injury threats depending on the current state of the robot and the human, a classification of these mechanisms, governing factors of the particular process and possible injuries are depicted in

Fig. 69.9. Physical contact can be divided into two fundamental subclasses: quasi-static and dynamic loading. Fundamental differences in injury severity and mechanisms are observed as well if a human is (partially) constrained or not, leading to the second subdivision. For the quasi-static case, it is differentiated between near-singular and nonsingular clamping as already outlined. The last differentiation separates injuries caused by blunt contact from the ones induced by tools or sharp surface elements.

Each class of injury is characterized by possible injuries (PI), worst-case factors (WCFs), and their worst-case range (WCR). WCFs are the main contributors to the worst case, such as maximum joint torque, the distance to singularity or the robot speed. The worst-case range indicates the maximum possible injury depending on the worst-case factors. In addition to the classification of injury mechanisms for each such class, suggestions for injury measures (IMs) are given as well. They are specific injury measures which are appropriate, useful for the classification and measurement of injury potentially occurring during the physical human–robot interaction. Please note that the list of injury measures is not necessarily complete, but these ones are certainly suitable to be applied to a more granular robotics injury analysis. This does not mean that criteria, such as the well-known head injury criterion (HIC), do not provide general insights; they are just not

Table 69.5 Impact data for the lateral surface of the right upper arm

Impact	Max. impact force (N)	Impact area (mm ²)	Displacement (m)	Tissue stiffness (N/m)	Stress σ (N/mm ²)	Impact velocity (m/s)	Kinetic energy (J)	Energy density (J/mm ²)	AO	VAS
1	9.5	966	0.03	316.7	0.001	0.2	0.08	0.0001	IC1MT1NV1	0
2	19	966	0.037	513.5	0.002	0.44	0.36	0.0007	IC1MT1NV1	0
3	38.1	966	0.044	865.9	0.039	0.65	0.80	0.0016	IC1MT1NV1	0
4	59.6	966	0.055	1083.6	0.062	0.88	1.45	0.003	IC1MT1NV1	0
5	81.4	966	0.058	1403.4	0.084	1.11	2.31	0.005	IC1MT1NV1	1
6	103.5	966	0.060	1725	0.107	1.34	3.37	0.007	IC1MT1NV1	1.5
7	128.1	966	0.064	2001.6	0.133	1.55	4.50	0.009	IC1MT1NV1	2
8	154.1	966	0.069	2233.3	0.16	1.76	5.81	0.012	IC1MT1NV1	3
9	186.4	966	0.069	2701.4	0.193	2.03	7.73	0.016	IC1MT1NV1	3
10	224.5	966	0.069	3253.6	0.253	2.24	9.41	0.019	IC1MT1NV1	4
11	272.2	966	0.077	3535.1	0.282	2.55	12.2	0.025	IC1MT1NV1	6

necessarily optimal to understand injury on a more differentiated lower-injury scale.

For example ① in Fig. 69.9 represents blunt clamping in the near-singular configuration (Fig. 69.9). Even for low-inertia robots, this situation could become dangerous and is, therefore, a possible serious threat with almost any robot on a fixed base within a (partially) confined workspace. Possible injuries are fractures and secondary injuries, for example, caused by penetrating bone structures or an injured neck if the trunk is clamped but the head is free. This would mean that the robot pushes the head further, while the trunk remains in its position. Another possible threat is shearing off a locally clamped human along an edge. Appropriate indices are, for example, the contact force and the compression criterion (CC) [69.49]. ③ in Fig. 69.9 represents the clamped blunt impact in nonsingular configuration. The injury potential is defined by the maximum actuation torque $\tau_{\max}$ and can range from no injury to severe injury or even death for high-inertia (and torque) robots. The robot stiffness does not contribute to the worst case since a robot without collision detection would simply increase the motor torque to follow the desired trajectory. Therefore, robot stiffness only contributes to the detection mechanism by enlarging the detection time. Also, the contact force and CC are well suited to predict occurring injury. ⑧ in Fig. 69.9 denotes the unconstrained impact which was the first injury mechanism investigated in the robotics literature. This process is governed by the impact velocity and (up to a saturation value) by the robot mass. As shown in [69.22], even a robot of arbitrary mass cannot severely injure a human head by means of impact-related criteria from the automobile industry like the head injury criterion (HIC). However, fractures, for example, of facial bones are likely to occur but not all would be classified as a serious injury. Laceration by

means of crushes and gashes are worth evaluating, especially with respect to service robotics. The contact force and CC are well-suited severity criteria for this class. In order to evaluate lacerations the energy density has to be considered.

The preceding overview is intended as a worst-case analysis for the described contact cases. The next step is to ask which actions can be taken against each particular threat [69.19]. At this point, however, it shall be noted that instead of quantifying injury in terms of a measurable injury criterion, injury evaluation by a medical expert, for example, via the AO-classification can always be applied and would presumably result in a more exhaustive and precise judgement.

69.2.2 Safety Standards for Human–Robot Interaction

Robotics standardization made significant progress to establish the underlying regulations for co-working cells in the real world. Safety for industrial robots is addressed in a variety of general standards [69.50–52]. The most important industrial robotics standards is the International Organization for Standardization (ISO) 10218. It was established in the recognition of the particular hazards that industrial robots and industrial robot systems may pose. The machinery concerned and the extent to which hazards, hazardous situations, and events are covered are indicated in the scope of ISO 10218. In recognition of the variable nature of hazards with different uses of industrial robots, ISO 10218 is divided into two parts. It provides a detailed analysis of mechanical hazards, such as impacts, crushing, shearing, entanglement, drawing-in or tapping, cutting or severing, and contact of persons with live parts (direct contact) [69.53]. In particular, the introduction of collaborative robots has been a ma-

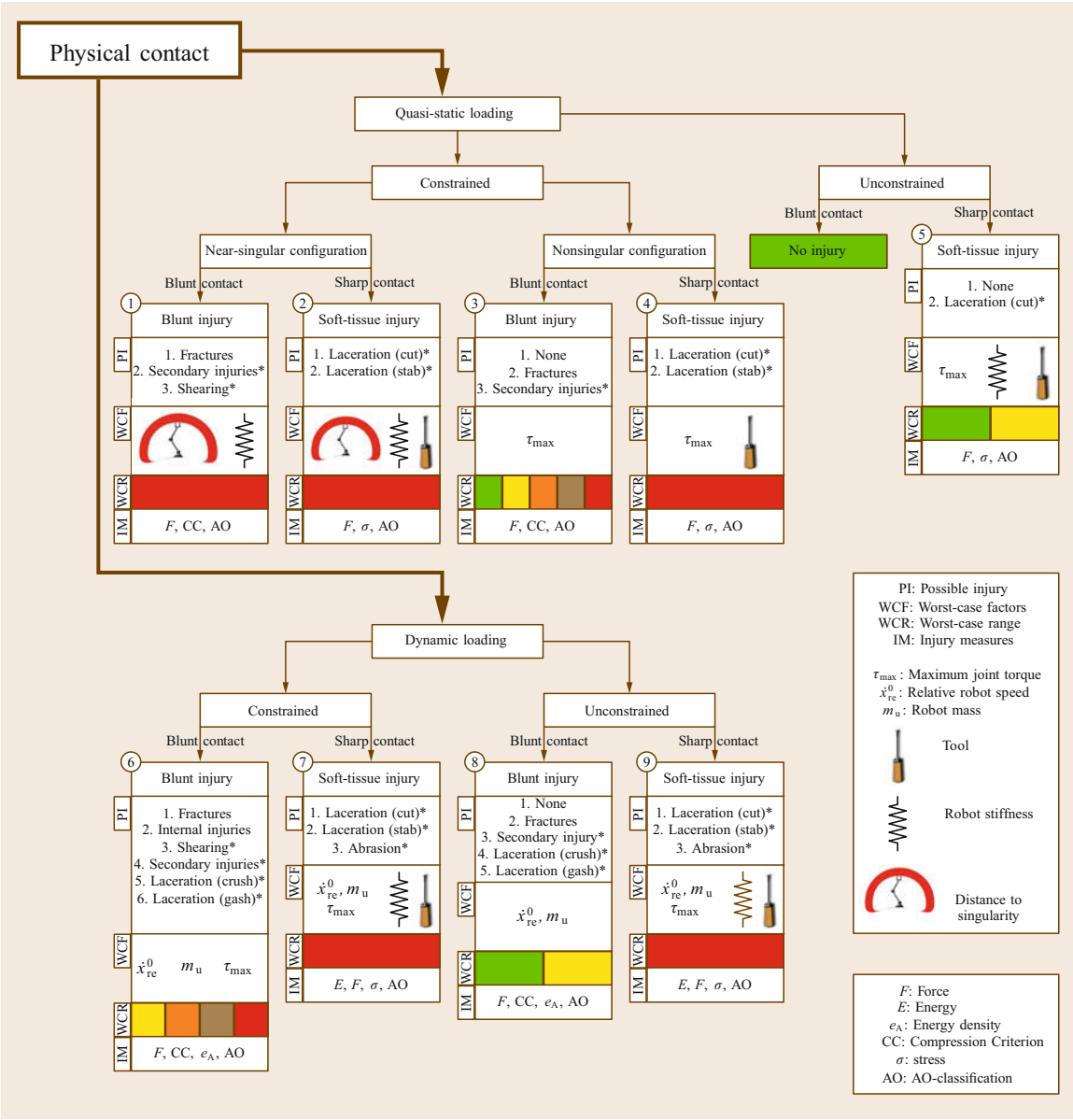


Fig. 69.9 Safety tree showing possible injury (PI), major worst-case factors (WCF) and the possible worst-case range (WCR). * indicates still ongoing topics of research. Additionally, relevant injury criteria are given for the head, chest, and soft-tissue injuries

for acknowledgment to the advances made in robotics research in pHRI over the last decade. The recent updates to ISO 10218 (safety requirements for industrial robots) led to the development of the new technical specification (TS) 15066. It is regarded as a complementary information that concretizes the content of ISO 10218. Generally, ISO/TS 15066 provides guidance for collaborative robot operation where a robot and a person share the same workspace. It considers collab-

orative modes and requirements, such as minimum separation distances, safety-rated monitored stops, speed and separation monitoring, and power and force limiting. In collaborative operations, the integrity of the safety-related control system is of major importance, particularly when process parameters, such as speed and force, are being controlled. A comprehensive risk assessment is required to assess not only the robot system itself, but also the environment in which it is

placed, that is, in the workplace. A key process in the elimination of hazards and reduction of risks is the design of the collaborative robot system and the associated cell layout. Various considerations about the access and clearance of the collaborative workspace are provided. During the design of a robotic system, the maximum space and the restrictions of the collaborative robot system have to be considered. Furthermore, the need for clearances around obstacles and the accessibility for operators should influence the design. The intended contact(s) between parts of the robot system and an operator plays a major role toward a possibly intrinsically safe design. In order to identify the risks resulting from the collaborative action, an appropriate set of collision incidents that can occur during the collaborative work activities and foreseeable misuse has to be determined. This has to include affected body regions and the involved collision areas of the robot. The limit values that may not be exceeded during the collision incident depend on the affected body regions. The geometry of the involved areas of the robot and the biomechanical properties of the affected body regions influence the forces occurring during the collision incident. Therefore, the [ISO/TS 15066](#) describes injury severity criteria that consist of maxi-

mum allowable limit values on individual body regions. These limit values are established to prevent the occurrence of skin/tissue penetrations that are accompanied by bleeding wounds, fractures, or other skeletal damage [69.54].

In addition to the industrial standardization efforts in the [pHRI](#) domain, the [ISO 13482](#) [69.55] is the first nonindustrial robot safety standard that allows/regulates close [pHRI](#). This international standard specifies requirements and guidelines for the inherent safe design, protective measures, and information for the use of so called *personal care robots*. It focuses on three types of personal care robots (mobile servant robots, physical assistant robots, and person carrier robots). These robots typically perform tasks to improve the quality of life of intended users irrespective of age or capability. The standard describes hazards associated with the use of these robots and provides requirements to eliminate or reduce the risks associated with these hazards to an acceptable level. Significant hazards are presented and this standard describes how they are to be dealt with for each personal care robot type. Robotic devices used in personal care applications are also covered by this standard and are to be treated as personal care robot.

69.3 Human–Friendly Robot Design

Designing robots for interaction has become a challenging subdomain in [pHRI](#), leading to novel devices that have one thing in common: active and/or passive compliance together with lightweight design being the central design paradigms. A number of research-focused robots have been designed specifically for [pHRI](#). The most important design guidelines, representatives, and modeling basics are outlined in this section. Apart from robots that are designed to act as general purpose co-workers, large robot assists with balanced, inertia reducing, cable-driven gantry systems can be used to create large payload robots that may be operated next to human workers [69.56].

69.3.1 Lightweight Design

In the process of making robots inherently suitable for close physical interaction with humans or only partially known environments, a design paradigm shift moving away from heavy, stiff, and rigid designs toward lightweight and highly integrated mechatronics designs has taken place. Low inertia and high (active) compliance have become desirable features, as has the use of

redundant sensing principles on the proprioceptive level (position, velocity, and torque).

General Characteristics

Generally, two major design approaches for lightweight robots have proven successful over the last years [69.57], namely the *mechatronics approach* and the *tendon-based approach*, respectively. Their commonalities are as listed:

- *Lightweight structures*: Lightweight, high-strength metals, or composite materials for the robot links. Moreover, the design of the entire system (controllers, power supply) is optimized for weight reduction to enable mobility.
- *Low power consumption*: This is mainly achieved by small moving inertias and accordingly designed motors.

Typically, *mechatronic robots* integrate electronics into the joint structure for allowing highly modular units. Such a design enables the assembly of different kinematics with increasing complexity, while keeping the respective joint philosophy. In terms of actuation,

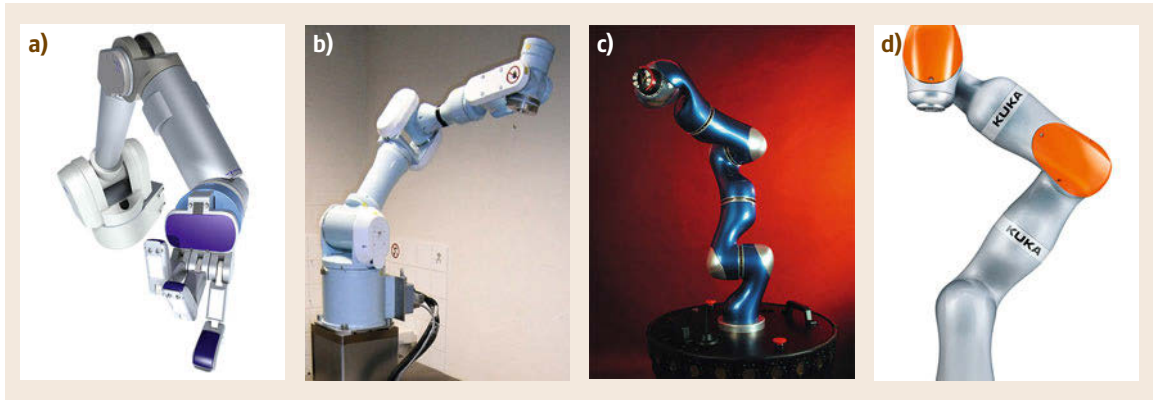


Fig. 69.10 (a) Barrett arm (after [69.58]), (b) Mitsubishi PA10 arm, (c) DLR lightweight robot III (after [69.59]), (d) KUKA LBR iiwa (after [69.60]) (courtesy of Barret Technology Inc., DLR, KUKA)

the combination of high power/torque motors with high transmission ratio gears is usually applied. From the proprioceptive sensing side, these systems are typically equipped with additional sensors, such as joint torque, force, and current sensing in addition to basic motor side position and current sensing only (Sect. 69.3.3).

Tendon-based robots have three major characteristics. First, they are typically equipped with remote direct drives. This reduces the overall weight of moving parts for a fixed base manipulator as the actuators are located in the robot base. For placing the actuators remotely from the base, cable-pulley systems are usually applied. Finally, low reduction ratios are used for keeping the system backdrivable. In turn, larger motors have to be selected, which adds additional total weight.

Another interesting class of compliant actuators is of note that implements compliance quite differently. They use rheological fluids such that they can alter their characteristic properties under the influence of either a magnetic or an electric field. A clutch between link and motor is operated in such a way that the output torque can be controlled. These actuators were also mo-

tivated and discussed from a human-safety perspective in [69.61].

Lightweight Robotic Systems

The most prominent robots that fall into the category of lightweight robots are depicted in Figure 69.10. The *Barrett arm* is a classic example of a *tendon-based design*, where the actuators are placed in the manipulator base and the joints are backdrivable due to the low reduction ratio. The *Mitsubishi PA10* arm was a commercially available lightweight redundant arm, with a weight of 38 kg and a payload of 10 kg. The fully torque-controlled *KUKA LBR iiwa* is based on the DLR lightweight robot technology [69.60]. Its third generation *DLR LWR-III* weighs 13.5 kg and is able to handle loads up to 15 kg, so an approximate unitary payload-to-weight ratio is achieved. The robot is equipped with joint torque sensors in each joint and has redundant position measurement (on motor and link side) [69.62].

Apart from single-arm robots as described above, various lightweight designs were also successfully integrated into research and commercial humanoid systems

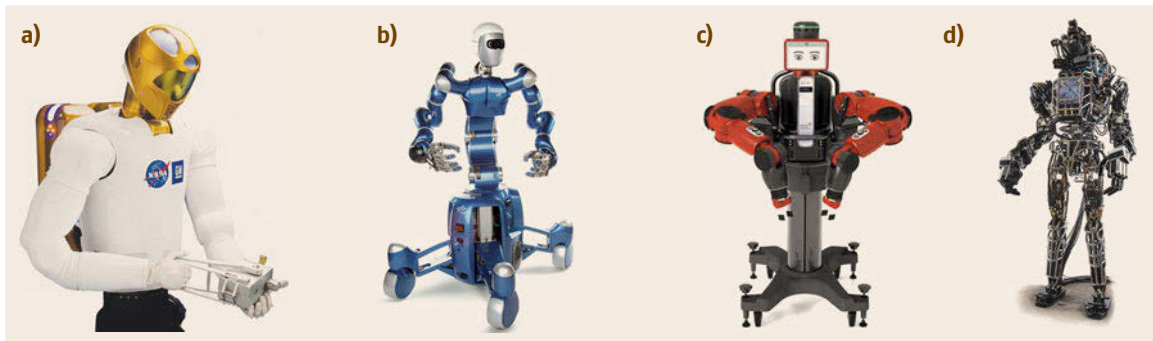


Fig. 69.11 (a) NASA Robonaut 2, (b) DLR Rollin' Justin, (c) Rethink Robotics Baxter and (d) Boston Dynamics Atlas (courtesy of NASA, DLR, Rethink Robotics Inc., Boston Dynamics)

(Fig. 69.11). The NASA (National Aeronautics and Space Administration) *Robonaut 2* [69.63], equipped with SEA, was originally designed for teleoperation and exploration in space [69.64]. The fully torque-controlled humanoid robot *TORO* [69.65], based on the DLR lightweight robot technology, has its origins in the upper body bimanual system *Justin* [69.66] (VIDEO 626). Rethink Robotics *Baxter* is a commercial two-arm upper body system for pick and place tasks that is equipped with SEA for torque measurement purposes. The hydraulically actuated humanoid, *Atlas* from Boston Dynamics, is one of the systems that entered the DARPA (Defense Advanced Research Projects Agency) *Robotics Challenge*.

Modeling Lightweight Robots

For a robot with n viscoelastic joints, the so-called reduced model of *Spong* [69.67] has become the standard way of modeling lightweight robots. When including also the presence of joint torques due to contact forces (on the link dynamics), we shall consider the following dynamic model of robots with viscoelastic joints:

$$\mathbf{M}(q)\ddot{q} + \mathbf{C}(q, \dot{q})\dot{q} + \mathbf{g}(q) = \tau_J + \tau_{\text{ext}}, \quad (69.10)$$

$$\mathbf{B}\ddot{\theta} + \tau_J = \tau. \quad (69.11)$$

The generalized coordinates are doubled since there will be a dynamic displacement $\delta = \theta - q$ between the motor positions $\theta \in \mathbb{R}^n$, as reflected through the gear ratios, and the link positions q . The matrix $\mathbf{B} = \text{diag}(B_i) \in \mathbb{R}^{n \times n}$ is the diagonal, positive definite motor inertia matrix. We define the *elastic joint torque* transmitted through the joints and coupling (69.10) and (69.11)

$$\tau_J = \mathbf{K}_J(\theta - q) + \mathbf{D}_J(\dot{\theta} - \dot{q}), \quad (69.12)$$

where $\mathbf{K}_J = \text{diag}(K_{J,i}) \in \mathbb{R}^{n \times n}$ is the diagonal, positive definite joint stiffness matrix, and $\mathbf{D}_J = \text{diag}(D_{J,i}) \in \mathbb{R}^{n \times n}$ is the diagonal, positive semidefinite joint damping matrix. The quantity τ_J in (69.12) is also the output of joint torque-sensing devices, when available. In many practical cases, the mechanical design of the transmission/reduction elements is such that one can neglect the joint damping, that is, $\mathbf{D}_J \simeq \mathbf{0}$. Joint elasticity has long been addressed for lightweight robot systems, however, more as an undesired consequence that the control has to handle [69.68]. This requires advanced control techniques in order to obtain accurate, performant motion. For a complete overview on the properties of robots with joint elasticity effects, please refer to Chap. 11.

69.3.2 Intrinsically Flexible Design

Recently, the class of intrinsically flexible actuators and robots have become increasingly popular. Inspired by the flexible properties in biological muscles, compliant joints are designed with the aim of imitating human or animal motions during various tasks. The main idea of intrinsically flexible actuation is to come closer to human capabilities in terms of speed and shock absorption. This is not realizable with today's rigid industrial robots, when assuming approximately the same torque range or weight as humans have. By storing and releasing energy in the joints, one aims for improvement in tasks, such as running or throwing [69.69–72] where humans still clearly outperform robots. In Chap. 21 and [69.73], a more in depth review of intrinsically flexible actuation is presented. In this chapter, we review only the relevant insights for placing the technology in the pHRI context.

General Characteristics

Roughly speaking, intrinsically flexible actuators can be divided into two categories:

- Actuators with fixed mechanical impedance, where the effective joint impedance is altered via active control. The most well-known example is the series elastic actuator (SEA) [69.74], whose acronym became a generic term for this class of actuators.
- Actuators where the impedance can be adjusted by altering mechanical joint properties, such as stiffness and damping. There exist various categories like variable stiffness actuators (VSAs) that allow stiffness changes or variable impedance ac-

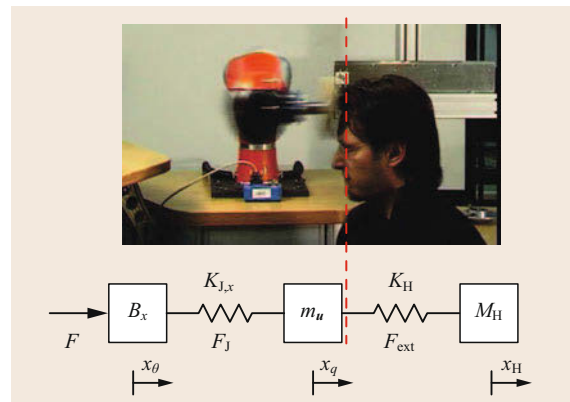


Fig. 69.12 Human–robot collision in operational space, which is defined by the reflected flexible dynamics of the robot and the local contact stiffness/mass properties of the human head

tuators (VIAs) that enable more general impedance changes, including damping adjustment.

The original motivation for introducing VSA and VIA, for example, in [69.20], was to make robots safer during unforeseen collisions due to dynamic decoupling of the motor and link-side inertia from each other. This effect reduces the collision danger by alleviating the impacting robot inertia. In [69.20], it is, for example, shown that HIC could be reduced by introducing elasticity in the joint. This idea was generalized and systematically analyzed in [69.75, 76], and is summarized here.

In order to simplify the human robot collision analysis basic models in operational space coordinates were used for this analysis (Fig. 69.12). For this, operational space coordinates and reflected inertias/stiffnesses along an arbitrary instantaneous impact direction $\mathbf{u}$ are considered [69.46]. The masses $M_H, m_u, B_x \in \mathbb{R}^+$ are the reflected human, link, and motor mass. $K_H, K_{J,x} \in \mathbb{R}^+$ are the reflected (human) contact stiffness and joint/structural elasticity. The projected human, motor, and link impact position are denoted by x_H, x_θ , and $x_q \in \mathbb{R}$, respectively. $x_\theta = p_u(T(\theta))$ and $x_q = p_u(T(q))$ are defined via the respective forward kinematics maps projected in the $\mathbf{u}$ -direction.

As pointed out in [69.20], a robot with quite low reflected link inertia $m_u = 0.1$ kg is able to reduce the impact forces significantly if a contact stiffness of $K_H = 5$ kN/m is assumed. Similar to the work in [69.21], it was shown that a decrease in joint stiffness can significantly reduce the impact characteristics and, thus, is a powerful countermeasure against large contact forces. In [69.77], it was deduced that for the case of a 2-DOF (degree of freedom) planar intrinsically compliant robot, already slightly touching a rigid wall with its second link, the compliant mechanism can limit the maximum static force/torque effectively if the motor torque is slowly increased. It is, of course, unquestionable that joint elasticity decouples the motor from the link. However, as was indicated in [69.22], a reduction in joint stiffness cannot reduce the impact characteristics during very rigid, fast, and blunt crash-test dummy impacts for a lightweight system, such as the LWR-III (which is basically an SEAs type robot from a modeling perspective). This was proven by measuring the decoupling of motor and link inertia via the integrated joint torque sensors and the additionally recorded external contact force.

Figure 69.13 depicts the experimental evidence for a collision at 1 m/s between a DLR LWR-III and a stationary unconstrained Hybrid III dummy (HIII) head on the frontal area [69.22]. The contact force f_{ext} was measured with a high-speed force sensor $f_{\text{ext,fs}}$ and for consistency check with a triaxial accelerometer $f_{\text{ext,as}}$.

As one can see, the simulation and experimental signals show very good consistency. Clearly, the projected elastic joint force f_j reacts delayed to the collision, thus proving the desired decoupling property already for such an intrinsically very stiff robot. For the impact simulation, a reflected stiffness of 6.72×10^4 N/m is chosen, which represents a realistic joint stiffness and structural elasticity value. The reflected motor inertia is $B_x = 13$ kg and the reflected link side inertia $m_u = 2$ kg. The dummy head mass is $M_H = 4.5$ kg and the contact stiffness is $K_H = 3.2 \times 10^5$ N/m.

This result showed that already the compliances of the built in gear and the joint torque sensor is sufficient to decouple the motor from the link, making it entirely unnecessary to further reduce joint stiffness for the given robot for this purpose. There are two main aspects, which have to be considered to fully understand this result. On the one hand, the contact stiffness of the crash-test dummy used is significantly larger than the reflected elasticity of the DLR LWR-III; however, it is also realistic for the human frontal area [69.27]. Furthermore, the reflected motor and link inertia for the DLR LWR-III are the same order of magnitude as for the human head mass. This is quite reasonable for a full-scale lightweight robot arm.

Two further benefits of inherent compliance are as follows. First, the robot itself is able to resemble compliant behavior without the inherent need for high-performance force/torque feedback. Please note that it is not possible to display arbitrary Cartesian stiffness behavior for a robot with diagonal stiffness matrix only [69.79]. Second, the joint elasticity acts in combination with the link inertia as a mechanical low-

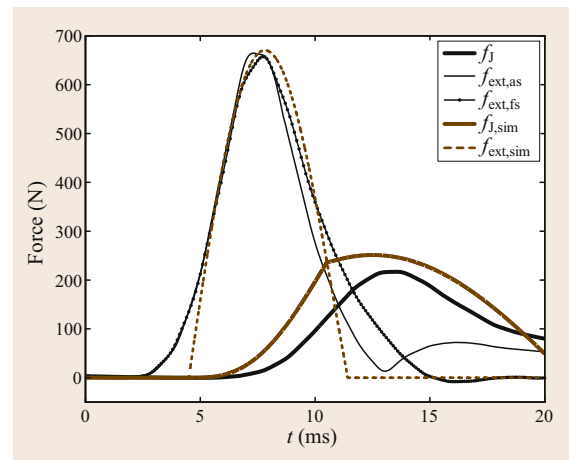


Fig. 69.13 Impact experiment and simulation of a LWR-III with a Hybrid III Dummy. The experimental contact force is measured for consistency check with a high-speed acceleration (as) and force sensor (fs) simultaneously

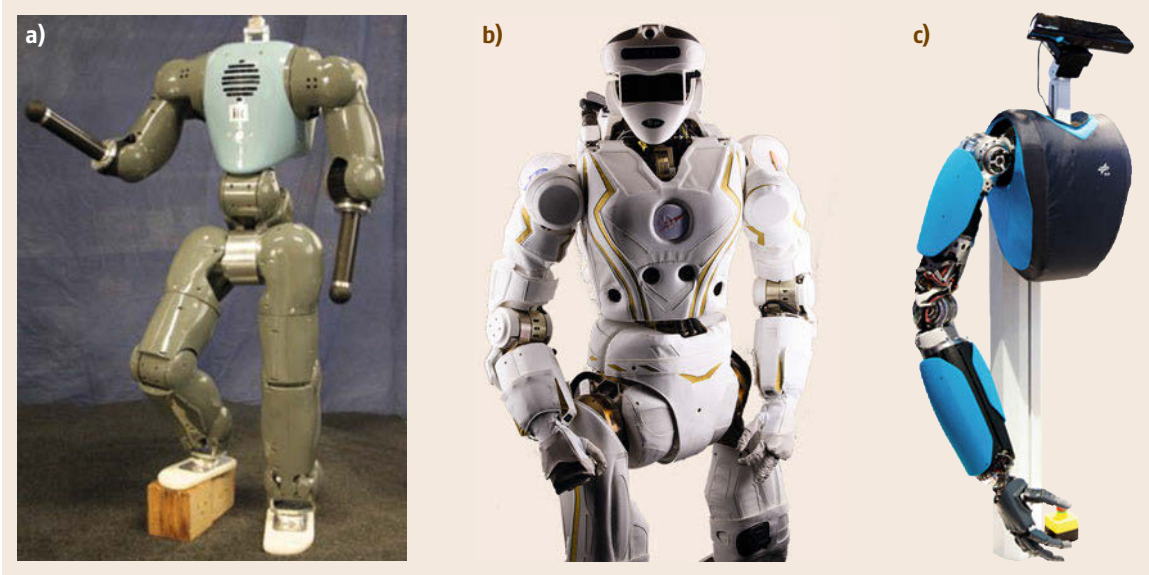


Fig. 69.14a–c Passively flexible anthropomorphic robots: compliant humanoid platform (COMAN, (a)) from IIT (after [69.78]), Valkyrie (b) from NASA, and hand arm system (HASY, (c)) from DLR (courtesy of IIT, DARPA, DLR)

pass filter, thus protecting the drive train from impact shocks; that is, it makes the system inherently more robust [69.71, 80].

Another interesting use of elasticities in the drive train of a manipulator relates to the fact that it can serve as a storage mechanism for potential energy, and be used to increase a robot's link speed beyond the maximum motor velocity [69.70, 71, 80–82]. This ability strongly influences the safety of intrinsically elastic systems, as a robot's impact speed determines its inherent collision danger to a large extent. However, we refer to [69.75] for further details on this matter, where the effect of a robot's elastic speed increase on potential danger in terms of HIC is derived.

Intrinsically Flexible Robotic Systems

Figure 69.14 shows some of the most prominent recent anthropomorphic/humanoid devices that employ passively compliant actuators. The COMAN system of IIT (VIDEO 624) is a full-scale SEA robot, as is NASA's Valkyrie. Both system's ability to measure torques results from the ability to flex around their joint axes and then relate this elastic deflection to the joint torque. The DLR hand-arm system [69.72] is fully equipped with VSA in every joint, while having approximately human size, strength, and dexterity.

Modeling Passively Flexible Robots

From a formal modeling point of view, lightweight robots and robots with fixed mechanical impedance are

very similar. The main difference lies in the respective torque sensor measurement principle. The joint elasticity in lightweight robots is rather high and allows only for small deflections between the motor and link position. The stiffness in compliant actuators, however, is intentional and typically at least an order of magnitude lower, thus enabling significantly larger deflections. Consider the elastic joint model (69.10) and (69.11) from Sect. 69.3.1, which under certain mild conditions also holds for intrinsically elastic robots. The main difference is that for lightweight robots, $K_{J,i}$ is large compared to SEA-like systems. For many VSA systems, the transmitted torque can be expressed as

$$\tau_J = f(\delta, \sigma), \quad (69.13)$$

where σ denotes a stiffness adjustment control input (typically the position of a second motor). The torque–displacement curve $f(\delta, \sigma)$ may exhibit different characteristics, such as being strictly increasing $\partial f(\delta, \sigma)/\partial \delta > 0$ and convex $\partial^2 f(\delta, \sigma)/\partial \delta^2 > 0$. More details on implementations can be found in [69.73].

69.3.3 Perception for Interaction

The recent advances in pHRI benefit greatly from previous achievements in contact and noncontact sensors and sensing techniques. In the current chapter, we shortly review the essential sensing techniques that had strong

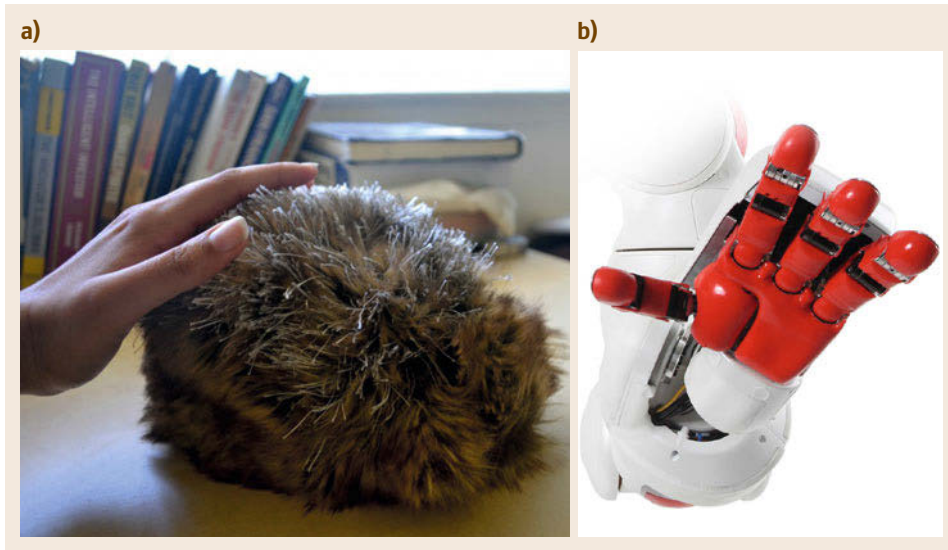


Fig. 69.15 (a) Furry robot *skin* utilizing piezo-resistive fabric and conductive sensors provides a low cost design concept with high tactile gesture recognitions rates (after [69.83]). (b) The hand of TWENDY-ONE with integrated distributed pressure sensors (courtesy of Karon MacLean, UBC, Shigeki Sugano Lab., Waseda University)

impact on pHRI and focus on the underlying main concepts. Chapters 28 and 32 give a full view and can be consulted for further details.

69.3.4 Proprioceptive Force/Torque Sensing

Many robot arms have the option to include a six-axis force/torque sensor at the wrist, enabling not only force control-based manipulation, but also symbolic haptic interaction [69.84, 85], possibly also based on joint torque sensing. More recently, torque sensors have been integrated into the joints of commercial robots, for example, into the KUKA LWR [69.86]. This allows for contact sensing along the entire robot structure with measurements of contact magnitude, direction, and knowledge of which link was contacted [69.87].

Essentially, two major sensing principles for joint torque measurement exist: either by directly measuring the torque which is typically done via strain gauges, or by measuring it implicitly via the deflections δ between link and motor position. For this, it is assumed that δ directly relates to torque typically by a constant multiplier, the joint stiffness $K_{J,i}$. For the latter, both link- and motor-side position sensors need to be mounted. The first works that aimed at developing and minimizing torque-sensing devices can be found in [69.88–90]. The torque-sensing principle has also a strong relation to the design classification in Sect. 69.3.

69.3.5 Tactile Perception

Several tactile skins have been developed over the years such as, for example, [69.91–94]. In the latter work, for example, the human skin served as a design metaphor. Therein, a solution of the goal conflict between the desired high sensitivity and the required mechanical robustness is in the focus. Furthermore, beyond providing the required sensory capability, the mechanical deformation and damping properties necessary for the operation of the robotic system are considered as well. Using whole-arm tactile sensing across the manipulator surface explicitly allows the sensing of multiple contacts; for example, in [69.95], the authors operate a robot in a cluttered environment in order to successfully reach a goal that is occluded by obstacles using a model predictive controller. Other recent examples of localized sensors include touch pads placed at key points on the robot [69.96], and force-sensitive resistors distributed over the robot [69.97]. The latter example is used in a novel haptic robot designed to both read and display emotion mediated through cues sensed primarily through physical interaction. These methods have the advantage of using reliable and fairly precise sensors, but are capable of measuring contact only at discrete locations. For more extensive contact sensing, several researchers have developed various types of robot skin; that is a distributed sensor network that covers extensive areas and measures diverse qualities of contact events, including location, magnitude, orientation, and temperature. Hard robot skins or shells have been used to

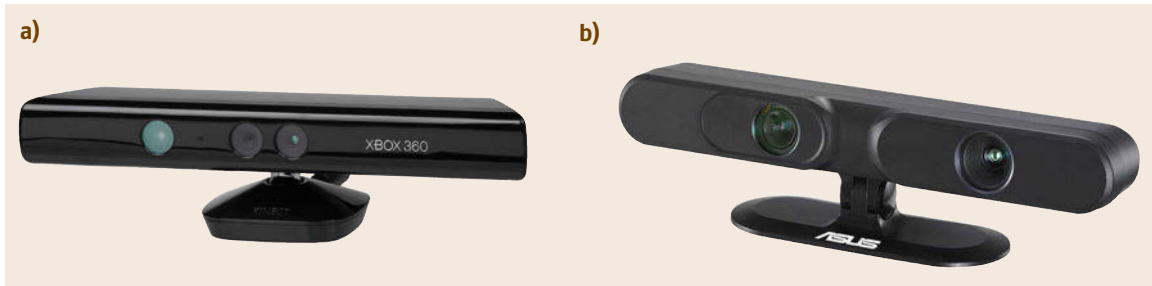


Fig. 69.16 Low cost 3-D-RGB-D cameras: (a) Microsoft Kinect (Wikipedia Commons), (b) Asus Xtion (courtesy Asus)

detect collisions [69.98], while soft robot skins that can conform to different robot shapes have been used for more complex, often social or affective, human–robot interaction, for example, [69.99]. While robot skin can add significant sensing capability to robots, it may also add to the complexity and cost, and thus compromises the robustness of the robot. However, recently a furry *creature* skin (Fig. 69.15) was created [69.83] using a combination of low-resolution piezo-resistive fabric, and conductive fur sensors to create a low-cost robot covering with 90% interaction gesture (stroking, patting, poking, hitting) recognition rates when trained on an individual and 68–80% recognition rates when trained on groups (👁️ VIDEO 615). A detailed review of tactile sensing technology for human–robot interaction can be found in [69.100]. Other examples can be found in Chap 28.

69.4 Control for Physical Interaction

For soft and safe pHRI, the question arises how to gently handle physical contact in robotics from a control point of view. As impedance control [69.103] became the most popular interaction control paradigm in the pHRI world, this particular scheme will be one focus of this section. Its generalization to multipriority impedance control laws allows the realization of sophisticated robot compliance with multiple objectives via active control. A major advantage of impedance control is that discontinuities like contact–noncontact do not create stability problems as they occur, for example, with hybrid force control [69.104]. Its extension to impedance and feed-forward learning and adaptation, for which the first works can be found in [69.105, 106], is discussed after introducing the concept of multipriority impedance control. Apart from nominal interaction control, a robot sharing its workspace with humans and physically interacting with its environment should be able to quickly detect collisions and safely react to them. In the absence of external sensing, relative

69.3.6 Visual Perception

Visual (noncontact) sensing is very important for preparing for pHRI. Tracking and planning for the location of a human partner and predicting, for example, the motion of the partner’s hand is an important precursor to a successful handover operations [69.12]. While well-known marker-based systems, such as Vicon and Optotrak systems, provide very high resolution tracking systems, they are impractical for day-to-day use. The development of low-cost 3-D-RGB-D (three-dimensional red green blue depth) cameras (Fig. 69.16) permits the 3-D tracking of full body models in large and partially occluded spaces, with ongoing improvements toward robustness in body pose tracking and for tracking of hand gestures [69.101, 102].

Motions between robot and environment/human are unpredictable and unexpected collisions may occur at any location along the robot arm. The state-of-the-art schemes for collision detection and reflex reaction are introduced. Finally, the last part of the section deals with the shared manipulation problem, one of the standard application examples of pHRI.

69.4.1 Interaction Control

Originally developed for robust and compliant object manipulation, impedance and the related admittance control (👁️ VIDEO 610) form a paradigm to treat robotic systems from an energetic point of view such that motion and force can be controlled in a unified manner. They offer the advantage over hybrid force-motion controllers to provide a framework independent from kinematic work space constraints. These control types popularized by [69.103] are also especially advantageous in terms of uncertainties and disturbances in

unknown environments due to their inherently robust nature [69.107]. The terms impedance and admittance, are derived from electrical system theory where they describe the relationship between voltage and current as input/output pairs. To generalize impedance and admittance such pairs can be defined domain-independently as effort and flow variables. For robotics, the mechanical analogies, that is, mechanical impedance and admittance are of particular interest.

More details on the conceptual basics of impedance and the dual admittance control can, for example, be found in [69.108, 109]. Furthermore, Chap. 9 gives a more thorough basis on force control strategies in general and impedance control in particular.

The mostly used version of impedance control is to impose a second-order dynamics of a mass–spring–damper system (so-called target impedance [69.103]) on the closed-loop equations. Typically, the control objective is expressed in operational space coordinates $\mathbf{x}$ as

$$\mathbf{M}_x \ddot{\tilde{\mathbf{x}}} + \mathbf{D}_x \dot{\tilde{\mathbf{x}}} + \mathbf{K}_x \tilde{\mathbf{x}} = \mathbf{F}_{\text{ext}}, \quad (69.14)$$

where $\tilde{\mathbf{x}} := \mathbf{x} - \mathbf{x}_d$ is the position error and $\mathbf{x}_d$ is called equilibrium position. $\mathbf{M}_x$ denotes the desired inertia, while $\mathbf{D}_x$ and $\mathbf{K}_x$ are the according closed-loop damping and stiffness matrices in operational space. $\mathbf{F}_{\text{ext}}$ denotes the external wrench acting at the end-effector of the robot. Assuming rigid body dynamics, the control law to obtain the aforementioned behavior is

$$\begin{aligned} \boldsymbol{\tau}_{C^*} = & \mathbf{g}(\mathbf{q}) + \mathbf{J}(\mathbf{q})^T [\boldsymbol{\Lambda}(\mathbf{q}) \ddot{\mathbf{x}}_d + \boldsymbol{\mu}(\dot{\mathbf{x}}, \mathbf{x})] \\ & - \mathbf{J}(\mathbf{q})^T [\boldsymbol{\Lambda}(\mathbf{q}) \mathbf{M}_x^{-1} (\mathbf{K}_x \tilde{\mathbf{x}} + \mathbf{D}_x \dot{\tilde{\mathbf{x}}})] \\ & + \mathbf{J}(\mathbf{q})^T [\boldsymbol{\Lambda}(\mathbf{q}) \mathbf{M}_x^{-1} - \mathbf{I}] \mathbf{F}_{\text{ext}}. \end{aligned} \quad (69.15)$$

In order to fully implement this scheme, a wrist force torque sensor is necessary for the inertia shaping part. In [69.110], a modified impedance controller was designed that uses angle/axis representations for the rotational components of the operational space. For its derivation, energy contributions with physical interpretation are considered and the end-effector orientation displacement representation is chosen to be in terms of a unit quaternion to avoid singularities.

For redundant robots, it is typically desired to also control the nullspace behavior in order to embed other control objectives $\boldsymbol{\tau}_{N,i}$ into a stacked hierarchy of tasks (Chaps. 17 and 36). For the case of a single nullspace controller $\boldsymbol{\tau}_N$, this torque has to be projected via the nullspace projector matrix $\mathbf{N}(\mathbf{q})$ into the nullspace of the task, leading to the overall control law

$$\boldsymbol{\tau}_C = \boldsymbol{\tau}_{C^*} + \mathbf{N}(\mathbf{q})^T \boldsymbol{\tau}_N. \quad (69.16)$$

The nullspace projection matrix can be chosen in different ways. The simplest case is $\mathbf{N}(\mathbf{q}) = \mathbf{I} - \mathbf{J}(\mathbf{q})^\# \mathbf{J}(\mathbf{q})$,

where $\mathbf{J}(\mathbf{q})^\#$ denotes the Moore–Penrose pseudoinverse. Alternatively, one may choose the *dynamically consistent* generalized pseudoinverse

$$\mathbf{J}(\mathbf{q})^\# = \mathbf{M}(\mathbf{q})^{-1} \mathbf{J}(\mathbf{q})^T \boldsymbol{\Lambda}(\mathbf{q}). \quad (69.17)$$

In particular, in the pHRI domain, a multitude of different subtasks $\boldsymbol{\tau}_{N,i}$ are meaningful to be executed simultaneously. These may, for example, involve:

- Safety (collision anticipation and avoidance, self-collision avoidance, ...)
- Physical constraints (joint limits, geometric task constraints)
- Task execution (tracking control, ...)
- Posture primitives (in particular for humanoids).

To realize consistent behaviors, task hierarchies are constructed such that certain tasks are prioritized over others [69.111]. In [69.112], a hierarchy is realized by null space projection techniques, which also prevents discontinuities concerning unilateral constraints by smoothing out transitions.

Extensions to the basic schemes for flexible joint dynamics [69.113–115] and for the SEA case [69.116] were developed as well. Furthermore, Cartesian impedance control has been applied to grasping and multiple-arm robotic systems in [69.117]. For a more in depth treatment of multipriority impedance control, please also refer to Chap. 67.

69.4.2 Learning and Adaptation

Close physical interaction between human and robot is a complex evolving process with high uncertainty and is hard to be modeled explicitly. Therefore, several learning and adaptation approaches were proposed to enhance a robot's capability and account for the inherently present uncertainty and unpredictability. In this sense, the extension of impedance control toward adaptive controllers that are able to learn and/or adapt the controller's impedance and feed forward torques is a challenging and rather recent research problem. Obviously, also the learning of the desired trajectories, for example, in terms of motion patterns became an important problem in this context. Generally, also collaborative tasks (Sect. 69.4.4) require learning either the impedance properties and/or certain trajectories such that the robot gains the ability to adapt its behavior to the human counterpart, or even guides it to guarantee successful collaboration. An important aspect of learning physical interactions is how to choose the right task coordinates and (meta-)parameters. This is essential to reformulate the otherwise high-dimensional problem spaces in a tractable form.

Since impedance control has already shown to be a valuable technique in cluttered and complex manipulation tasks, recent research focuses on the adaption of the impedance characteristics to further improve the robot capabilities during interaction. Iterative learning control techniques belong to the first methods that have been investigated to tackle difficult manipulation problems [69.118, 119]. However, they do not only require the exact same repetitive motion of the manipulator, but also to account for unforeseen changes in the environment due to force inconsistencies which are particularly present in pHRI. Other early approaches include, for example, the use of neural networks in impedance control to counteract disturbances and environmental uncertainties [69.120]. An approach to adapt force, trajectory, and impedance simultaneously has been presented in [69.121] as a biomimetic controller. It is constructed based on studies in neuroscience that show that humans adapt feedforward and feedback forces as well as their impedance in order to learn unstable tasks in daily life. According to [69.122], the principles of motor learning are:

1. Motor commands to perform a desired action are composed of both feedforward commands, defined as the component of the motor command learned by repeating an activity, and feedback commands.
2. Learning is performed in muscle space.
3. Feedforward increases with the muscle stretch in previous trial.
4. Feedforward also increases with antagonist muscle stretch.
5. Feedforward decreases when the error is small.

Mathematically, these principles can be expressed as follows [69.105]. Generally, the central nervous system tends to minimize the motion error as well as the metabolic cost such that no extra effort will be spent on the learned impedance and feedforward torques. This can be expressed by minimizing the joint-level cost function

$$V(t) = \frac{1}{2} \int_{t-T}^t \tilde{\Phi}^T(\sigma) \mathbf{Q}^{-1} \tilde{\Phi}(\sigma) d\sigma + \frac{1}{2} \epsilon(t)^T \mathbf{M}(\mathbf{q}) \epsilon(t). \quad (69.18)$$

Therein, $\mathbf{Q}$ is a positive definite weighting matrix corresponding to the learning rates; $\tilde{\Phi}$ is defined as the difference between the instantaneous value

$$\Phi = [\text{vec}(\mathbf{K}_q(t))^T, \text{vec}(\mathbf{D}_q(t))^T, \tau_{ff}(t)^T]^T \quad (69.19)$$

and the required optimal value Φ^* , that is, $\tilde{\Phi} = \Phi - \Phi^*$. The quantities ϵ , $\mathbf{K}_q$, $\mathbf{D}_q$, and τ_{ff} denote the track-

ing control error [69.123] and the values to be learned, namely, the closed loop joint space stiffness, damping, and feed forward motor torques. For the joint stiffness adaption law, this leads for example to

$$\begin{aligned} \delta \mathbf{K}_q(t) &= \mathbf{K}_q(t) - \mathbf{K}_q(t-T) \\ &= \mathbf{Q}_{\mathbf{K}_q} [\epsilon(t) \epsilon(t)^T - \gamma(t) \mathbf{K}_q(t)], \end{aligned} \quad (69.20)$$

where $\gamma(t) > 0$ is a constant forgetting factor and $\mathbf{Q}_{\mathbf{K}_q}$, which is contained in $\mathbf{Q}$, is a symmetric positive definite matrix corresponding to the learning rate of the stiffness. T is a time constant to denote task periodicity. In an analog manner, adaption for feedforward torque and damping can be deduced, which results in the following control law,

$$\begin{aligned} \tau_c(t) &= \tau_{ff}(t) - \mathbf{K}_q(t) \epsilon(t) - \mathbf{D}_q(t) \dot{\epsilon}(t) \\ &\quad - \mathbf{L}(t) \epsilon(t) + \tau_r(t) \end{aligned} \quad (69.21)$$

$$\epsilon = \dot{\epsilon}(t) + \kappa \epsilon(t), \quad (69.22)$$

where $\tau_r(t)$ compensates for robot/arm dynamics and bounded noise. The term $\mathbf{L}(t) \epsilon(t)$ ensures a certain stability margin. The overall control law flow chart is depicted in Fig. 69.17. A stability proof of this approach can be found in [69.105]. An open problem with this method that remains to be unsolved is how to automatically select the meta parameters, such as the forgetting factor γ . A similar approach was developed in [69.124], where impedance adaptation laws were tested on a two-robot collaboration task. The robots lift together a beam after a task model was learned. A different approach based on the perturbations of the robot imposed kinesthetically by a human teacher such that the stiffness of the robot is adapted is investigated in [69.125]. Finally, the so-called teleimpedance paradigm [69.126] aims to remotely controlling the robot via the human arm reference position and impedance.

Learning task trajectories has been a rather well-studied field for several years now. For example, in [69.127], the authors examined the task of learning collaborative lifting of an object using hidden Markov models (HMM) and Gaussian mixture regression. Task demonstration was done via a haptic interface that controlled the robot hand. HMMs are also used in [69.128] in order to learn semantic task structures during a joint task execution. A semantic label of recognized task segments is acquired from a human partner by using speech recognition. Tasks in pHRI where transitions from contact to noncontact situations arise have been examined in [69.129]. Therein, marker data is used to obtain motion primitives. These are then updated with contact time information, comprising a low-level layer of learning. In addition, there is a high-level layer, which selects

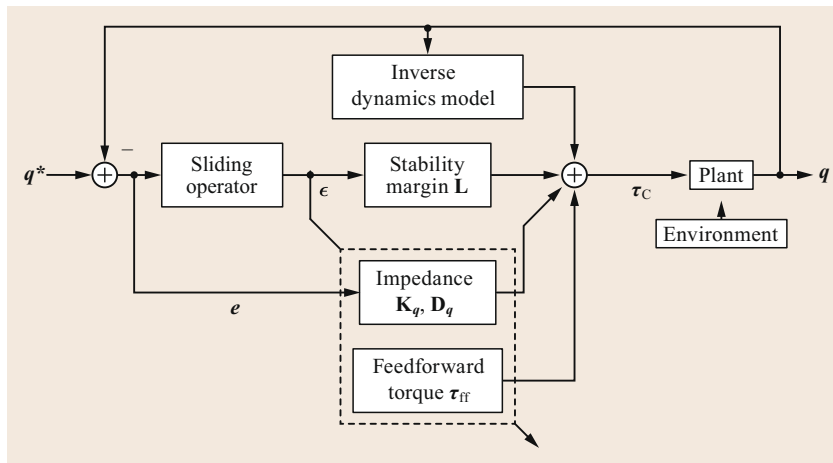


Fig. 69.17 Control diagram of the biomimetic adaptive impedance controller from (after [69.105])

a motion primitive and an end-effector reference position. Again, both layers are encoded via **HMMs** to provide a suitable abstraction, which is a key when dealing with high-dimensional spaces.

In [69.17], dimensionality reduction for learning was employed to realize assistive tasks, such as helping a robot to stand-up or walk. This principal component analysis (**PCA**)-based reduction lets the learning take place in a low-dimensional joint manifold instead of the original high-dimensional space. It reduces the complexity of the learning domain for multidegree-of-freedom systems such as humanoids. A recent approach to learning trajectories based on human preferences was proposed in [69.130], where machine-learning techniques were applied to derive the optimal behavior from human action ratings during runtime. Figure 69.18 shows how the robot learns to handle a knife safer by receiving low rewards from the human if the dangerous tool is moved in undesired orientations and/or trajectories.

69.4.3 Collision Handling

One of the core problems in **pHRI** is the handling of collisions between robots and humans, with the primary motivation of limiting possible human injury due to physical contacts. Various *monitoring signals* can be

used to gather context independent information about the event.

The *collision detection phase*, whose binary output denotes whether a robot collision occurred or not, is characterized by the transmission of contact wrenches, often for very short impact durations. The occurrence of a collision, which may happen anywhere along the robot structure, shall be detected as fast as possible. A major practical problem is the selection of a threshold on the monitoring signals, so as to avoid false positives and achieve high sensitivity at the same time. A heuristic approach is to monitor the measured currents in robot electrical drives, looking for fast transients possibly caused by a collision [69.131, 132]. Another proposed scheme compares the actual commanded torques (or motor currents) with the nominal model-based control law (i.e., the instantaneous torque expected in the absence of collision), with any difference being attributed to a collision [69.133]. This idea has been refined by considering the use of an adaptive compliance control [69.134, 135]. However, tuning of collision detection thresholds in these schemes is difficult because of the highly varying dynamic characteristics of the control torques.

Knowing which robot part (e.g., which link of a serial manipulator) is involved in the collision is an important information that can be exploited for robot



Fig. 69.18 The robot Baxter learns to safely handle a knife ([69.130]; courtesy of Saxena's Robot Learning Lab)

reaction. *Collision isolation* aims at localizing the contact point $\mathbf{x}_c$, or at least which link i_c out of the n -body robot collided. One way to obtain both collision detection and isolation is to use sensitive skins [69.91–94]. However, it would obviously be more practical and reliable to detect and possibly isolate a collision without the need of additional tactile sensors. On the other hand, the previously mentioned monitoring signals used in [69.131–135] are in general not able to achieve reliable collision isolation (even when robot dynamics is perfectly known). In fact, they either rely on computations based only on the nominal desired trajectory, or compute joint accelerations by inverting the mass matrix and thus spreading the dynamic effects of collision on a single link, or use acceleration estimates for torque prediction and comparison, which inherently introduces noise (due to double numerical differentiation of position data) and intrinsic delays. The common drawback of these methods is that the effect of a collision on a link propagates to other link variables or joint commands due to robot dynamic couplings, thus affecting the isolation property.

Other relevant quantities about a collision that are deduced during the *collision identification phase* are the directional information and the intensity of the generalized collision force, either in terms of the acting Cartesian wrench $\mathcal{F}_{\text{ext}}(t)$ at the contact, or of the resulting joint torque $\boldsymbol{\tau}_{\text{ext}}(t)$ during the entire physical interaction event. This information characterizes (in some cases, completely) the collision event. The first method that simultaneously achieved collision detection, isolation, and identification was proposed in [69.136]. The basic idea was to view collisions as faulty behaviors of the robot actuating system, while the detector design took advantage of the decoupling property of the robot *generalized momentum* $\mathbf{p} = \mathbf{M}(\mathbf{q})\dot{\mathbf{q}}$ [69.137, 138].

During the *collision reaction phase*, the robot should react purposefully in response to a collision event, that is, taking into account available contextual information. Because of the fast dynamics and high uncertainty of the problem, the robot reaction should be embedded in the lowest control level. For instance, the simplest reaction to a collision is to stop the robot. However, this may possibly lead to inconvenient situations, where the robot is unnaturally constraining or blocking the human [69.19]. To define better reaction strategies, information from collision isolation, identification and classification phases should be used. Some examples of successful collision reaction strategies have been given in [69.87, 139].

Collision Detection and Identification

A recent overview on standard techniques to estimate $\boldsymbol{\tau}_{\text{ext}}$ can be found in [69.26]. In this chapter,

we focus on the main method, namely the monitoring method based on the observation of the generalized momentum that was introduced in [69.136]. The scheme, which is regarded as the standard algorithm, was motivated by the desire of avoiding the inversion of the robot inertia matrix, decoupling the estimation result, and also eliminating the need of an estimate of joint accelerations. The according disturbance observer-based estimator for the rigid case is defined as

$$\mathbf{r}(t) = \mathbf{K}_O \left\{ \hat{\mathbf{p}}(t) - \int_0^t [\boldsymbol{\tau} - \hat{\boldsymbol{\beta}}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{r}] ds - \hat{\mathbf{p}}(0) \right\}, \quad (69.23)$$

with $\hat{\mathbf{p}} = \hat{\mathbf{M}}(\mathbf{q})\dot{\mathbf{q}}$, $\hat{\boldsymbol{\beta}}(\mathbf{q}, \dot{\mathbf{q}}) = \hat{\mathbf{g}}(\mathbf{q}) + \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} - \hat{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}}$, and $\mathbf{K}_O = \text{diag}(k_{O,i}) > 0$ being the diagonal gain matrix of the observer. Under ideal conditions, $\hat{\mathbf{M}} = \mathbf{M}$ and $\hat{\boldsymbol{\beta}} = \boldsymbol{\beta}$, the dynamic relation between the external torque $\boldsymbol{\tau}_{\text{ext}}$ and $\mathbf{r}$ is

$$\dot{\mathbf{r}} = \mathbf{K}_O(\boldsymbol{\tau}_{\text{ext}} - \mathbf{r}). \quad (69.24)$$

In other words, $\mathbf{r}$ is a stable, linear, decoupled, first-order estimation of the external collision torque $\boldsymbol{\tau}_{\text{ext}}$. Large values of $k_{O,i}$ give small time constants $T_{O,i} = 1/k_{O,i}$ in the transient response of that component of $\mathbf{r}$, which is associated with the same component of the external joint torque $\boldsymbol{\tau}_{\text{ext}}$. In the limit, we obtain

$$\mathbf{K}_O \rightarrow \infty \Rightarrow \mathbf{r} \approx \boldsymbol{\tau}_{\text{ext}}. \quad (69.25)$$

Collision Reflex Reactions

After a collision has been detected, suitable collision reflex reaction is needed. Four basic context-independent joint-level collision reflexes are discussed next. They lead to significantly different reflex behavior after a contact was detected. In the third and fourth schemes, the directional information on contact torques provided by suitable identification schemes such as (69.23) may be used to safely drive the robot away from the collision location.

Robot Stop. The most obvious strategy to react to a collision is to stop the robot. This behavior can, for example, be obtained by setting $\mathbf{q}_d = \mathbf{q}(t_c)$, where t_c is the instant of collision detection or by simply engaging the robot's brakes. More elaborate braking strategies can be found in [69.140].

Torque Control with Gravity Compensation. One may also react to a collision by switching the controllers. Typically, prior to the collision incident, the

robot moves along a desired trajectory with a position reference-based controller (e.g., position or impedance control). After detection, the control mode is switched to a compliance-based controller that ignores the previous task trajectory. A particularly useful variant is to switch to torque control mode with gravity compensation $\tau = \hat{g}(q)$ (VIDEO 611). Note that this strategy does not explicitly take into account any information about τ_{ext} .

Torque Reflex. This strategy extends the torque control-based strategy by explicitly incorporating the estimation or measurement of τ_{ext} into the motor torque τ via

$$\tau = \hat{g}(q) + (\mathbf{I} - \mathbf{K}_r)\tau_{\text{ext}}, \quad (69.26)$$

where $\mathbf{K}_r = \text{diag}\{k_{r,i}\} > 1$. It can be shown that, under sufficiently accurate estimates or measurements, such a law is equivalent to scaling of the robot dynamics by $\mathbf{K}_r^{-1}$. The closed-loop dynamics become

$$\underbrace{\mathbf{K}_r^{-1}\mathbf{M}(q)}_{\mathbf{M}'(q)}\ddot{q} + \mathbf{K}_r^{-1}\mathbf{C}(q, \dot{q})\dot{q} + \tau_{\text{ext}} = \mathbf{0}, \quad (69.27)$$

where $\mathbf{M}(q) > \mathbf{M}'(q)$ holds component-wise.

Admittance Reflex. Reference trajectory modification via an admittance-type strategy that uses the measurement or estimation of τ_{ext} can easily, for example, be realized via

$$q_d(t) = - \int_{t_c}^T \mathbf{K}_a \tau_{\text{ext}} dt, \quad (69.28)$$

where $\mathbf{K}_a = \text{diag}\{k_{a,i}\} > 1$. With this scheme that requires no control switching the robot quickly drives away from the external torque source and decreases the contact forces till they decay to zero.

69.4.4 Shared Manipulation Control

Collaborative carrying, particularly of a long, large, heavy or flexible object, is a common scenario in pHRI research (Fig. 69.19). As discussed earlier, Cobots represent the parallel case where passive robotic devices control the path along which a shared load will be transported, but give their operator full control of load motion along that path (Chaps. 39 and 70; VIDEO 821). Most shared manipulation schemes utilize some form of impedance control [69.142]. In an early work, the authors of [69.143, 144] proposed an impedance controller with speed-dependent damping coefficients. The

authors of [69.145] employed a similar approach (with fixed virtual impedance) to control the horizontal movement of their Mobile Robot Helper's mobile base in response to applied forces of a human user on the other end of a cooperatively carried load (VIDEO 606). The authors of [69.144] also described a lifting controller employing a pair of cascaded second-order virtual admittance controllers. Due to the raising/lowering of a cooperatively carried load the applied torques on an admittance-controlled, high-stiffness wrist generate a wrist deflection that translated (via a fixed gain) into a virtual vertical force. This force raised or lowered the robot end effector via a second admittance controller. In [69.141], an admittance controller was presented that was tuned for human preference, which is typically slightly underdamped. In [69.146], an admittance strategy was used to translate user force input into robot steering commands within a constrained trajectory.

Ideally, in cooperative manipulation, robotic and human partners will naturally take turns with leading and following roles depending on the state of a shared task. A switching model for haptically linked human-robot pairs that allows the robot to continuously vary its behavior from *completely following* to *completely leading* was introduced in [69.16]. In [69.147], the authors presented a mathematical treatment of the cooperative load manipulation problem to allow one or more robots to carry a load with a human user along a desired trajectory. They also incorporated variable leading behavior in the robots, enabling them to just steer the load (following) or completely control the load's axial motion (leading).

More recently, Evrard's homotopy approach was applied to load lifting, enabling the robot assistant to vary its behavior between leading and following based on its confidence in its predictions of the human user's



Fig. 69.19 Collaborative lifting experiment with a long object (after [69.141])

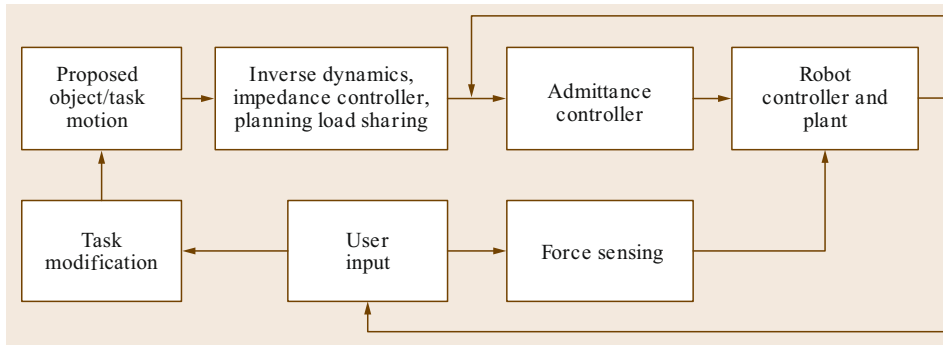


Fig. 69.20
Generalized
schematic for
collaborative task
control

intentions [69.15] (VIDEO 617). These are monitored through the kinematics of the shared load. Recently, an admittance control law that guarantees the stability of the robot during constrained motion and also provides a quite intuitive human interaction was designed in [69.148]. The admittance law uses the time derivative of the contact force between the human and the robot to estimate human intent and an online estimate of the interaction stiffness resulting in very accurate shared-control of the robot system. In [69.149], the authors developed and user tested an interactive controller

for a collaborative carrying task, utilizing a strategy to model effort sharing between the robot and the user. A generalized schematic for admittance-based collaborative task control is depicted in Fig. 69.20. On the motion planning side, minimum jerk trajectories [69.150] have been used to generate robot trajectories that are well matched to the motion of the human partner, and require the human to use less energy in the interaction, for example, [69.151]. Results from [69.152] indicate that a simpler quintic trajectory was also suitable for this purpose.

69.5 Motion Planning for Human Environments

The definition and quantification of injury, pain, or general risk are essential to express what safe behavior really means. The according insights can also be applied to generate safer robot motions such that injury and risk prevention are explicitly taken into account at this level. Two main branches of motion planning algorithms for danger reduction were developed, which are described hereafter.

69.5.1 Biomechanically Safe Motion Planning

As mentioned in the beginning of the chapter, human collision safety has to be ensured from an injury biomechanics perspective. Safety could, for example, be defined as *ensuring that only mild contusions may occur in worst case scenarios*. The natural question that arises is now how to formally respect such a metric, that is, how should a robot be controlled so that an unforeseen contact remains subcritical according to the underlying injury biomechanics or pain data. For this the authors of [69.25] gave the schema, termed safe motion unit (SMU), to link basic data to intrinsically safe robot velocity. The basic idea is to represent any data or general insight in a (possibly purely data driven) functional relation, linking impact properties to human

injury or pain. With this, it is possible to calculate the instantaneous safe robot velocity given the robot's inertial properties, surface curvature, and possible human body parts it might collide with

$$\begin{aligned} &(\text{mass, velocity, geometry, body part}) \\ &\rightarrow \text{observed injury/pain} . \end{aligned} \quad (69.29)$$

For the injury/pain metric, multiple international classifications exist from which one may choose from. In [69.25], for example, the AO-classification was used. Thereafter, a careful set of experiments, or if possible simulations, can be generated to deduce the relation of interest. Each experiment should be designed such that the impacting mass, its velocity, and curvature are known in addition to any supplementary sensory readings of interest. Furthermore, the observed, measured, or calculated injury and/or pain level of the involved body part has to be quantified according to the selected scale. To restrict the amount of experiments to a feasible number, the impactor geometry is assumed to be composed of different basic geometric primitives (spheres, cuboids, corners). Thus, a finite set of so-called *safety curves* can be constructed, which represent fitted threshold curves for a given injury indicator in

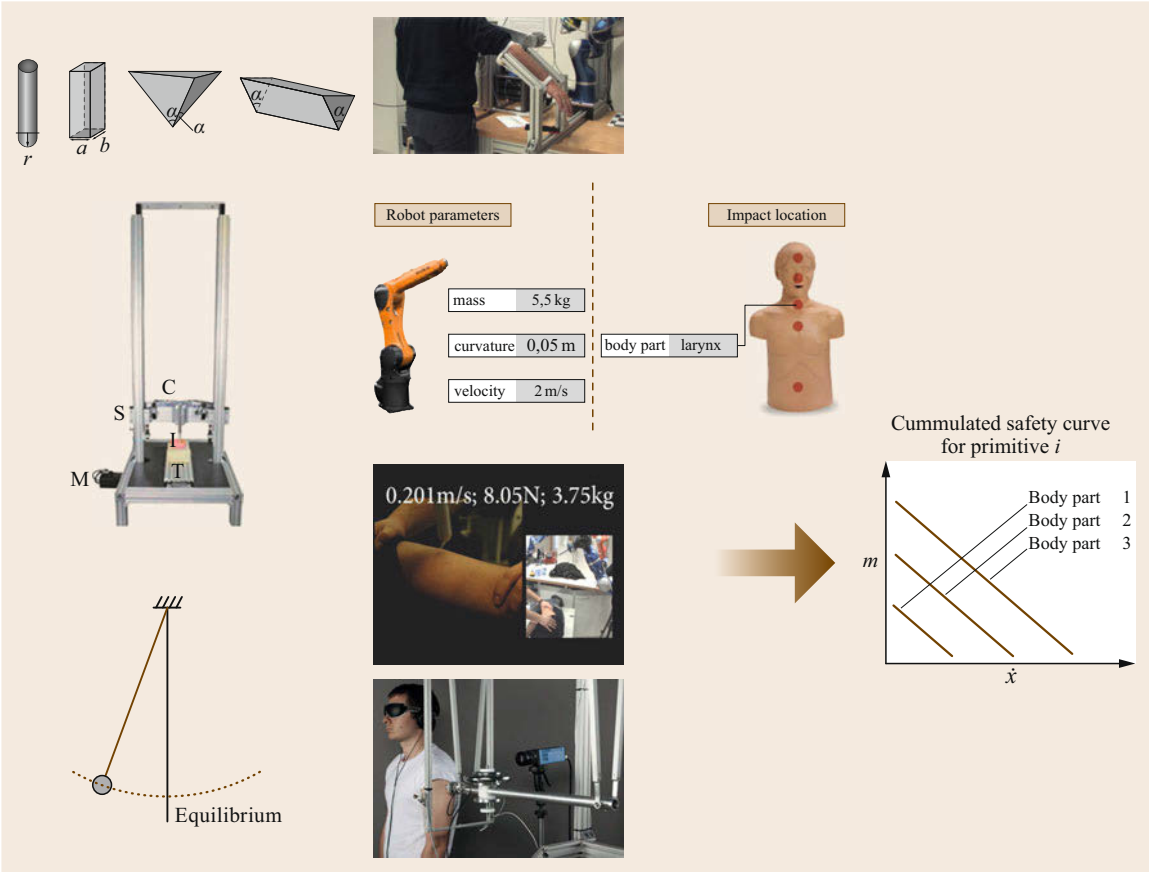


Fig. 69.21 A unified view: From collision experiment/simulation to cumulative *safety curves* for biomechanically safe robot velocity

the mass–velocity space parameterized by the body part (Fig. 69.21).

This idea can now be applied to a robot for safe velocity generation (Fig. 69.22). The concept is to scale any desired velocity command $\dot{q}_d$ by α to a biomechanically safe value $\dot{q}_d^*$. The scalar α is computed from evaluating the instantaneous robot inertial and local surface properties with respect to their injury potential. For this, the effective mass m_{POI} in the respective u -directions of the relevant points of interest (POIs) are

ically safe value $\dot{q}_d^*$. The scalar α is computed from evaluating the instantaneous robot inertial and local surface properties with respect to their injury potential. For this, the effective mass m_{POI} in the respective u -directions of the relevant points of interest (POIs) are

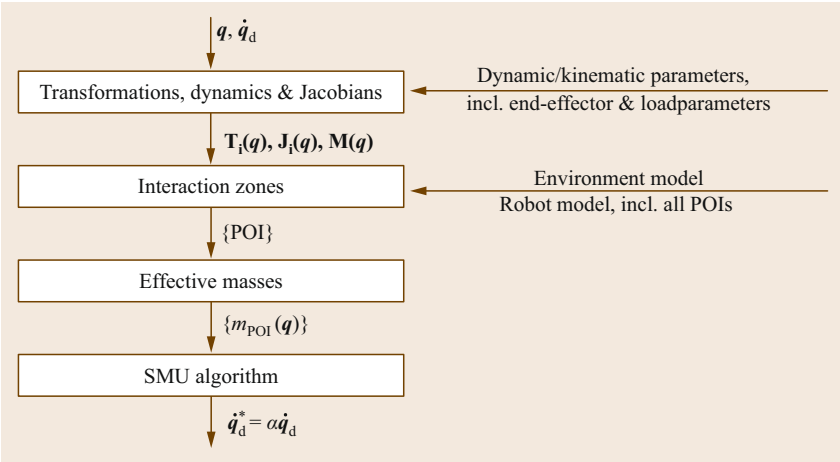


Fig. 69.22 Pipeline for creating biomechanically safe velocities based on the SMU algorithm (after [69.25])

evaluated via (69.7). Each POI is associated with a surface geometry primitive that is then used to link the respective POI to some underlying biomechanical injury, pain, or risk *safety curve*.

69.5.2 Risk–Metric–Based Motion Planning

As discussed in Sect. 69.4.3, there are numerous techniques for detecting impacts or potential collisions during pHRI. Collision monitoring methods can be used to ensure that forces and torques, or more simply the energy, of the robot system are limited during a collision event. To ensure safe and human-friendly interaction in unstructured environments, additional safety measures, utilizing system control, and planning are required.

Since physical interaction itself is a collision, a key problem of human-safe planning and control methods is to identify when human safety is actually threatened. In [69.154], a danger evaluation method was developed using the potential impact force as an evaluation measure. In this work, several danger indices were proposed based on the design properties of the robot. This danger index can be defined as a product of factors which affect the potential impact force between the robot and the human, such as distance, relative velocity, robot inertia, and robot stiffness. The authors applied this index as an objective function for improved mechanical design, control, and motion planning. A danger index based on estimated impact forces for a potential collision between a robot and a human was computed in [69.155] and used as an input to a real-time trajectory generation system, which balances the goal seeking with potential danger. In [69.153], the same authors combined their system with a vision based and physiological monitor-

ing system, which allows the robot to respond to the user's real-time position and attentiveness. During the interaction, the user is monitored to assess his level of approval of the robot's actions while the trajectory planner monitors safety factors, such as robot velocity and user intent. Finally, the safety control module provides a real-time response to short-term horizon factors evaluated by a *safety measure estimation module* (Fig. 69.23).

For mobile service robots, the authors of [69.156] proposed a collision avoidance controller based on estimates of user behavior, using a *social force* model to determine whether the user intends to avoid the collision or not so that the robot can respond accordingly. In [69.157], the authors introduced a method using so-called kinetostatic danger fields as a metric for the danger which the current posture and velocity of a robot pose to objects in its environment. The work presented in [69.121] shows an algorithm which maximizes the productivity of an industrial robotic manipulator while guaranteeing a safe human–robot distance. In addition to the relative human–robot distance, it takes also dynamic and control characteristics into account. In [69.158], the authors proposed a method based on an intuitive physical interpretation, namely, an impedance-like second-order motion generation. It is designed to provide safe motion in complex environments, taking into account both proximity to objects, and external forces. A method that achieves collision avoidance for a redundant robot while permitting the end-effector task to continue is presented in [69.159]. Using data from a 3-D-RGB-D camera, this method is purely based on computations of distances between the robot body and dynamic obstacles in the workspace (e.g., the user) that are processed through a *risk function* to adjust the joint

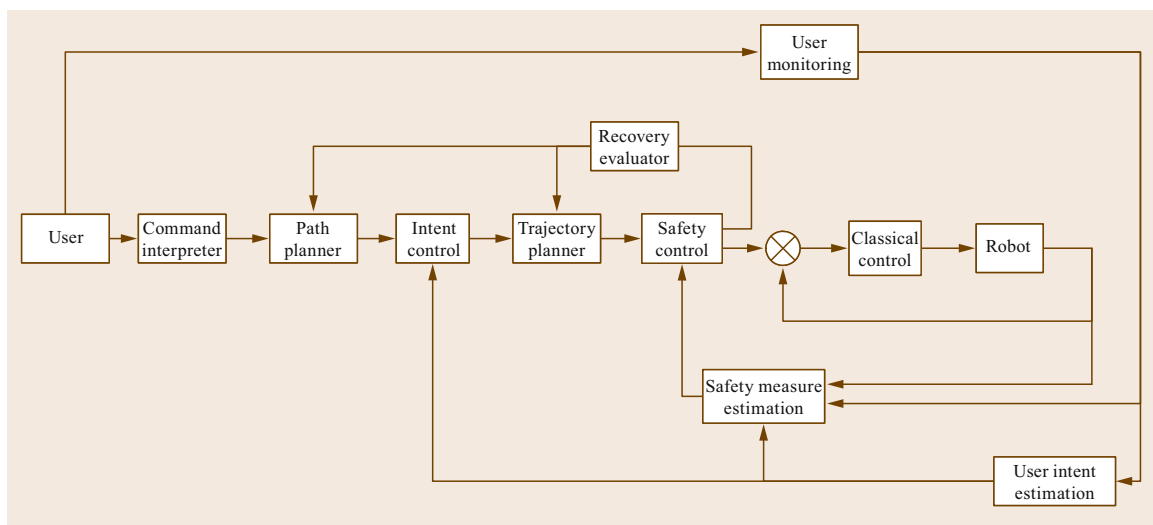


Fig. 69.23 Schematic of motion planning system with user intent and safety monitoring input (after [69.153])

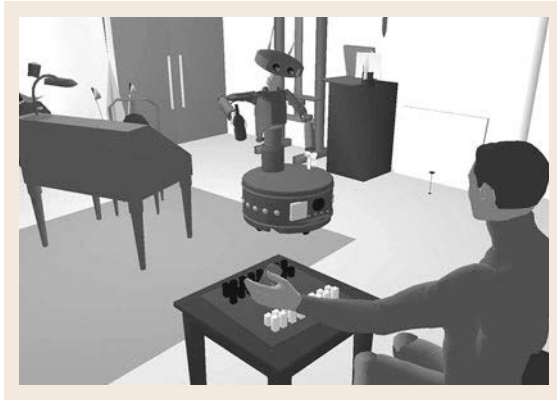


Fig. 69.24 Human-aware motion planner of Laboratoire d'analyse et d'architectures des systèmes (LAAS) (after [69.160]; courtesy of Rachid Alami)

velocities. The motion task of the end effector is modified by an artificial potential field-type method.

69.6 Interaction Planning

In order to profit from the collaboration of human and robot by combining the flexibility, knowledge and sensory skills of a human with the efficiency, strength, endurance, and accuracy of a robot, according interaction planners need to be designed to plan their joint actions for a common goal. In the interaction planning domain, the central question is how to plan robot human joint actions and reactions in a certain interaction process, involving also unexpected environmental changes, one of the most basic ones being the human entering the robot's workspace. The definition of the interaction planning problem and the integration of reflex reaction schemes that potentially lead to an abrupt deviation from nominal course have to be elaborated. On an architectural level, the incorporation of *reactivity* has to be systematically represented.

69.6.1 Collaborative Action Planning

Approaches to subproblems of the full interaction planning problem were addressed in the literature. In [69.163], for example, the system SHARY for human-aware task planning was introduced. It produces social plans of a task by implementing communication schemes to negotiate the task solution with the human partner.

In [69.164], dynamic neural fields (DNFs) were used to build a decision-making system for interac-

69.5.3 Human-Aware Motion Planning

Applying and extending classical motion planning techniques to the problem of human-robot interaction was originally done in [69.160]. The authors developed a human aware mobile robot motion planner, which incorporates humans accessibility, their vision field, and their preferences in terms of relative human-robot placement (Fig. 69.24). Human dynamics were integrated into the algorithm.

Extensions of the original work toward a motion planner for pHRI scenarios were elaborated in [69.161]. Therein, certain constraints, such as distance, visibility, and comfort are taken into account to generate safer motions and were demonstrated within a handover scenario. The algorithm has been extended to cluttered environments in [69.162], where a randomized cost-based exploration method provides an initial path that is relevant with respect to pHRI and workspace constraints.

tion in cooperative human-robot tasks. The main idea is to let the robot imitate human behavior in order to make the cooperation between robot and human appear rather intuitive. A structural overview of the system is depicted in Fig. 69.25. A vision system observes the scenery and recognizes task-related objects and gestures of the human coactor. Object positions are stored in the *object memory layer*. The *action observation layer* decides which type of known action was executed by the coactor. The expected outcome of this action is then simulated by the *action simulation layer* and thereafter passed to the *intention layer*. Here, the intention of the coactor is determined. The knowledge about the coactor's intention and the expected outcome of his actions is used by the *common subgoal layer*. It contains prior knowledge about the task structure and the subgoals to be achieved for task completion. The *common subgoal layer* is responsible for enabling actions that lead to the fulfillment of a currently achievable subtask only. Based on the information coming from the *intention layer* and the *object memory layer*, the *action execution layer* decides to perform an action, which supports the human in the intended subtask or leads to the completion of an independent subtask and does not interfere with the current human intention. Each layer of the system is formalized by one or more DNFs. The activity $u_i(x, t)$ at time t of a neuron x is described by the differential

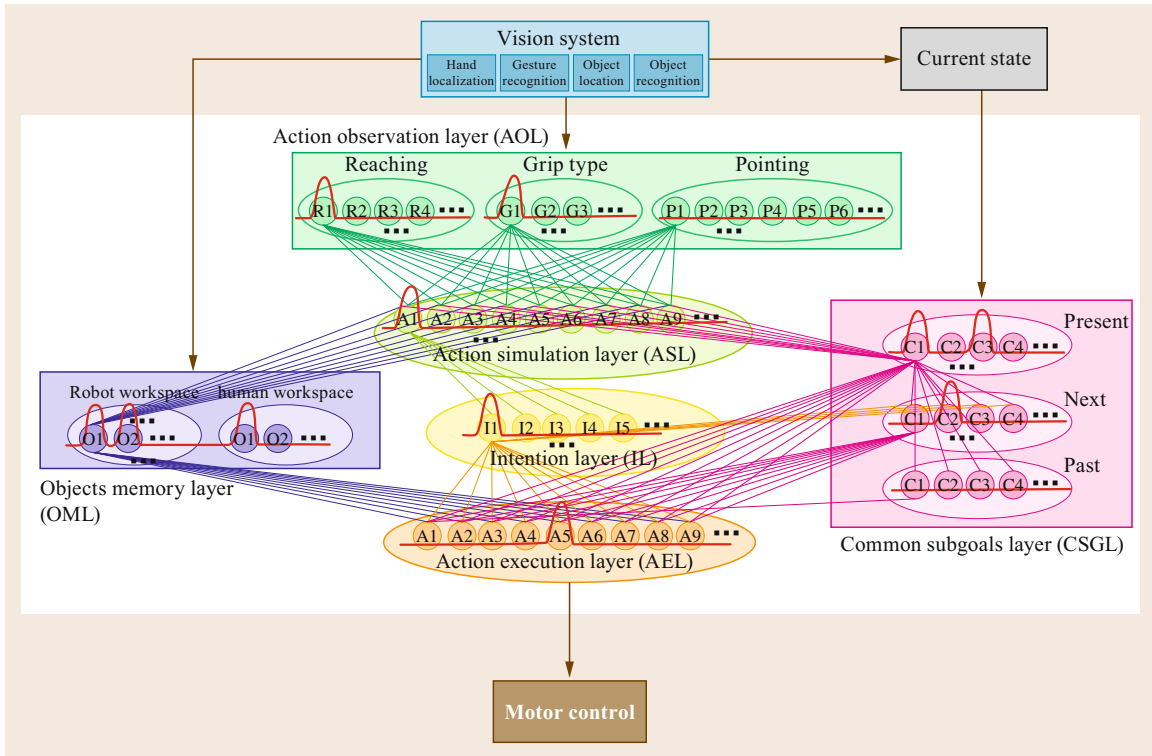


Fig. 69.25 Structural overview of the decision-making system from (after [69.164]; courtesy of Estella Bicho)

equation

$$\tau_i \frac{\delta u_i(x, t)}{\delta t} = -u_i(x, t) + S_i(x, t) + \int w_i(x - x') f_i(u_i(x', t)) dx' - h_i, \quad (69.30)$$

where $\tau_i > 0$ and $h_i > 0$ denote the timescale and the resting level of the field dynamics, respectively. S_i is the summed input to a local population. The output function f_i is chosen to be a sigmoid function and the interaction strength $w_i(x - x')$ is a Gaussian curve, which depends only on the distance between x and x' (Fig. 69.26).

In [69.129], a mimetic communication model for pHRI is introduced, where the according motion primitives are taught by human demonstration via marker control. These are subsequently encoded into hidden Markov models (HMMs) and allow the robot to execute them and even to recognize the motion primitives executed by the human partner. Based on the motion primitives, interaction primitives are then learned as chains of actions and reactions. The flow of interaction primitive learning is depicted in Fig. 69.27a. First, the robot executes a motion primitive, followed by ob-

serving the human's respective reaction in order to learn the correct interaction pattern sequence. After this step, the motion primitives are updated and the process is repeated. The underlying scheme of interaction is shown in Fig. 69.27b. The learned motion primitives are encoded as continuous HMMs (CHMMs) and form the middle layer of the system. They are then used to recognize the motion primitive executed by

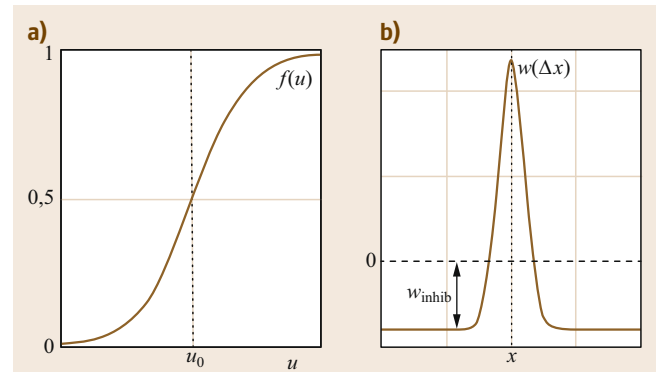


Fig. 69.26 (a) Nonlinear threshold output function that maps activity to a sigmoidal with threshold u_0 . (b) Synaptic weight function for modeling the interaction strength between any two neurons x and x' in (69.30) (after [69.164]; courtesy of Estella Bicho)

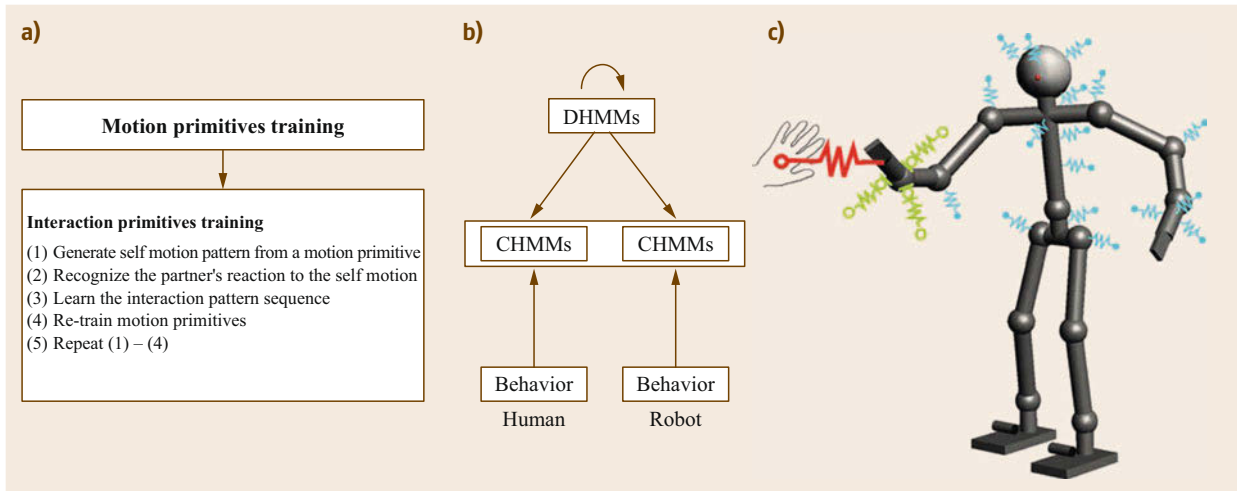


Fig. 69.27 (a) Learning of interaction primitives. (b) Scheme of interaction. (c) Adaption of robot motion via virtual spring (after [69.129]; courtesy of Dongheui Lee)

the human and to generate the motion of the robot according to the interaction primitives encoded as discrete **HMMs** (**DHMMs**) at the top. The robot motion (more precisely its behavior in the context of the authors' work) may then be modified to adapt to human motion in the real world (expressed by the thin horizontal arrow). The bold horizontal arrow represents the assumed adaption of the human to the robot behavior. The adaptation strategy of the robot movement is depicted in Fig. 69.27c. For this, an impedance controller is used in combination with a virtual spring connected to the robot hand to attract the device into the correct position. Figure 69.28 depicts an application of the interaction scheme, where the robot high- or low-fives a human coactor with one or two hands, respectively.

69.6.2 Interaction Planning Problem

In order to formalize the interaction planning problem, one needs to be able to describe the entire scenario, the system state of the robot, the state of the human(s) (possibly including future behavior prediction of both), the environment state including all relevant objects and the overall abstract task state. This information about the world state comprises the concept of an *interaction*

world, which builds the basis for formulating the general *interaction planning problem*.

Definitions

The set of *world states* **WS** is defined as

$$\mathbf{WS} = \mathbf{RS} \times \mathbf{HS}^n \times \mathbf{OBS}^m \times \mathbf{TS}, \quad (69.31)$$

where **RS**, **HS**, **OBS**, **TS** denote the set of the robot states, n humans, m obstacles, and an overall task state, respectively.

The set of *robot states*

$$\mathbf{RS} = \mathbf{S} \times \mathbf{RA}^n \times \mathbf{IR} \quad (69.32)$$

contains information about the internal state $s \in \mathbf{S}$ of the robot, the robot awareness $ra \in \mathbf{RA}$, and the interaction state $ir \in \mathbf{IR}$. The interaction state of the robot may, for example, take the values *autonomous*, *collaborative*, or *cooperative*. The robot awareness indicates its ability to predict human actions. The set of internal states $\mathbf{S} = \mathbf{S}_{ac} \times \mathbf{S}_b \times \mathbf{S}_p$ contains information about the set of actions carried out by the robot $\mathbf{S}_{ac}$. Furthermore, the behavior set $\mathbf{S}_b$, which includes, for example, controller choices and respective parameterizations, reflex reactions, and type or parameterizations of trajectory

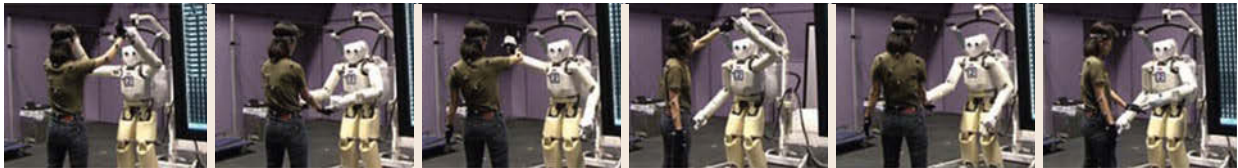


Fig. 69.28 pHRI using the mimetic communication model (after [69.129]; VIDEO 625; courtesy of Dongheui Lee)

planners. Such a reflex reaction which can be thought of as an analogy to human reflexes, intends to bring the robot to a safe state or even a reflex cascade R (Sect. 69.6.3). Finally, the physical state $sp \in S_p$ contains, for example, the robot's instantaneous position, velocity, and momentum.

The set of *human states*

$$HS = PSH \times PA \times HA \times IH \times D \quad (69.33)$$

combines the sets of physical state PSH (position, velocity, etc.), personal attributes PA (fitness, age, experience, etc.), human awareness HA (the ability of the human to predict the robots actions), interaction states of the human IH (for example, *waiting for robot*, *work with robot* or *work without robot*), and the distances D between human and robot. In its most simple nontrivial case, D could, for example, consist of the elements *in workspace*, *in perception*, *out of perception*, and *lost perception*.

The set of *task states*

$$TS = A \times TC \times IS \quad (69.34)$$

contains A , TC , IS that denote the sets of possible actions, task criticality, and expected interaction between human and robot, respectively. The task criticality specifies the effect of potential task failure on human safety. A task consists of the meaningful composition of actions and/or more complex skills such as *grasp object* or simply *move to pose* according to a particular creation process.

The Interaction Planning Problem

The *interaction planning problem* then denotes the problem of selecting a suitable, and if possible optimal, robot action and associated behavior in every time step based on the information contained in the world state, the history of the process HIS , and available (dynamic) knowledge stored in a knowledge base KB (for example, safety knowledge, object properties, world grounding rules, ...). Formally, this can be expressed by the *select action mapping*

$$sa : WS \times HIS \times KB \rightarrow S_{ac} \times S_b. \quad (69.35)$$

Optimality could, for example, be expressed in the following *reinforcement learning* sense, where the selected behavior shall lead to a maximum reward. This is obtained as follows:

1. A *task evaluator* evaluates the suitability of a particular action/behavior for fulfilling the desired task.
2. A *safety evaluator* evaluates the overall safety of the situation by taking into account different biomechanical injury criteria, the expected interaction

between human and robot, human–robot–related geometric quantities, such as minimal distance, as well as the task criticality.

3. Finally, additional rewards may be given by the human in order to capture human-friendly behavior.
4. The overall reward is then a suitable combination of the basic rewards.

69.6.3 Robot Reflexes

Human reflexes are involuntary reactive body movements in response to a perceived input, the so-called stimulus, that is, one does not even have to *think about what to do*. In humans, reflexes aim for body protection. Based on built-in heuristics, they automatically protect the human body from injury. However, the exact separation in terms of hybrid system-like theory is not yet clear. Thus, the line between discrete reflex states and according systemic responses on both electrical and mechanical levels is somewhat blurred. In robotics, on the other hand, it is possible to separate these levels and extend the concept of basic *nominal robot actions* by *reflex reactions* [69.9, 85, 139]. These concepts systematically incorporate the possibilities one gains from the already described collision detection and reflex reaction schemes (Sect. 69.4.3). Other work in similar directions for developing human-like withdrawal reflexes can be found in [69.165].

In contrast to the classical planning and execution pipeline, the activation of reflexes that are able to override the nominal task plan due to environmental or internal conditions that do not comply with nominal task behavior have to be considered. In contrast to humans, these reflexes do not necessarily have to be fixed (or slowly time-varying over learning cycles). On the contrary, they may be tailored to every nominal action such that local context dependency (in particular instantaneous sensory input) may be taken into account. After instantaneous reactions are executed, the main problem is to decide what to do next. Either local re-entry into the previous plan or entire re-planning have to be executed. Figure 69.29 depicts the overall concept also in the context of task and interaction planning.

Formally, a robot reflex is associated with a suitable activation signal. Typically, this represents either the indication of a certain stimulus or a fault. Stimuli are general perception inputs, whereas faults are detected either by processed stimuli (observation of external torques, proximity information, etc.) or general system malfunctions as, e.g., communication collapse or runtime violations. Even rather complex reflex patterns can be activated that may be represented as directed reflex graphs, i.e., a decisional component in the inner most

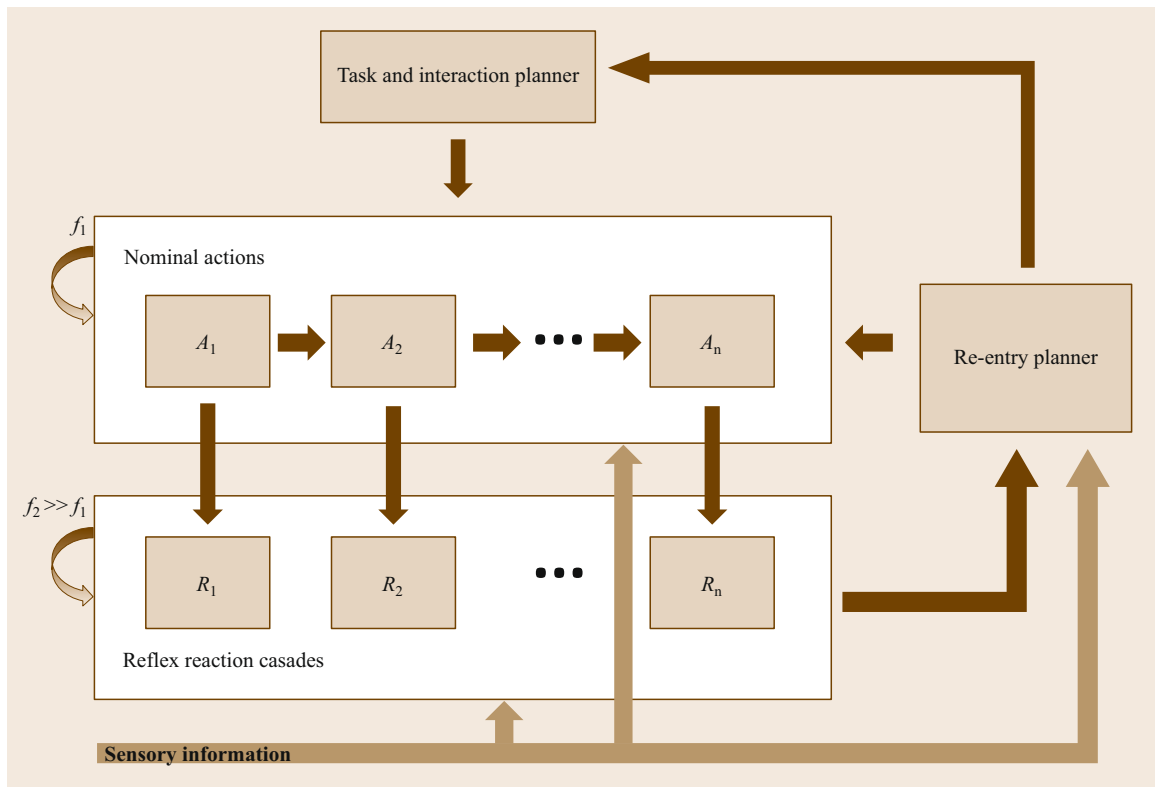


Fig. 69.29 Conceptual sketch of robot reflexes; f_1 and f_2 indicate the update rates, or alternatively the system bandwidth of the nominal planning and execution as well as the reflex reaction level. Typically, the former acts at a much lower frequency than the latter one (after [69.85, 139])

control loop of the system. A still relatively open research problem is how to resolve potential failures after reflexes were triggered by planning suitable re-entering and continuation of the task.

69.6.4 Reactive Control Architecture

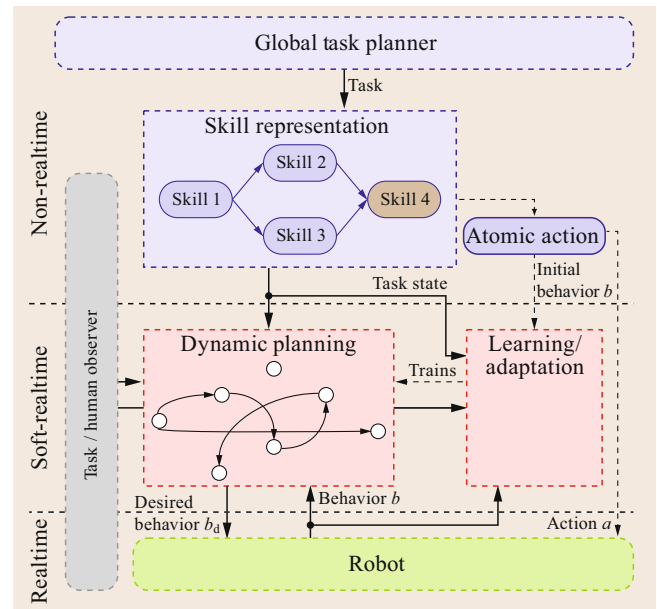
Obviously, the diverse methods and complex requirements in the pHRI domain and more specifically from interaction control, reflex planning, human-centered motion planning, and interaction planning make new architectural concepts necessary. The central requirements to an according control architecture become rather different from the classical ones (Chap. 12) due to the demands for very responsive behavior not only on control but also on planning level. Figure 69.30 depicts such a reactive control framework [69.166] (VIDEO 616). One of the main questions to address is how to adapt dynamically, safe, and task consistent, while keeping the overall plan and the respective context in mind. The control framework is composed of three layers of abstraction operating at different time scales:

1. On the highest level of abstraction a *global task planning* module builds global task plans that contain temporo-logical concatenations of robot skills, which are derived from any suitable task planning language. Typically, this module runs either offline, in particular when building an entire nominal task plan that contains interaction schemata, or at very slow update rates of several seconds or minutes, depending on the complexity and novelty of the respective task. Skills are topologically invariant capability structures, which instantiations can be modified in terms of skill parameter vectors. The most basic skill is the atomic robot action that represents the formal interface to the robot real-time control core and mechatronics. More complex skills can, e.g., be *grasp an object* or *hand over an object*. Each skill itself is aware of the current task state and which atomic action is currently being executed. This information is then sent to the *dynamic planning layer*.
2. The second layer of abstraction, the *dynamic planning level* is capable of executing and/or modifying plans dynamically, which means that it shall run at least in the range of $\approx 1\text{--}10\text{ Hz}$. It is responsible

Fig. 69.30 Reactive and human-friendly control framework for acting in partially known environments and interaction ►

for selecting the best action under the premise of the current task state, human state and behavior, as well as the environmental state. In a *learning and adaptation* unit the global task knowledge is translated into the respective dynamic planning domain language, i. e., global knowledge and plans are encoded into a dynamic level such that dynamic adaptation can make use of global context and the respective mission. The according reactive planning unit is then able to (re-)plan the robot's desired nominal actions such that safe, yet task consistent actions, are executed if possible. In particular, instantaneous perception may cause alterations of the original global plans. A major task on this abstraction level is to change the preplanned course of action safely and task consistently. However, finding its way back into the task is at least equally challenging and requires careful treatment (re-entry planning).

3. The lowest architectural layer is the *low-level (real-time) control layer*. Typically, this is subdivided into multiple hierarchical layers, involving also the reflex machine (Fig. 69.29). However, for sake of clarity, we consider it to be a single consistent representation that is accessible via a desired action/behavior complex (a_d, b_d) that is sent to the system for execution. As the desired behavior may alter due to reflex behaviors in case of accidental events such as unforeseen collisions, the control



layer feeds back the currently active action/behavior pair (a, b), such that the *dynamic planning layer* is able to react accordingly.

Fundamental to the aforementioned architecture is the capacity to observe human actions on various levels of abstraction. In this sense, a *human observer* that gathers all relevant information and knowledge about human agents is essential. In particular, it provides human-related information that can be of further use.

69.7 Conclusions and Challenges

pHRI has become a central discipline in robotics over the last decade. This is due to the significant progress made in the fields of mechatronics, interaction control, motion planning, and 3-D sensing toward highly integrated and sensorized lightweight systems that are able to physically interact with their surrounding. In direct consequence the learning, planning, and execution of safe and legible interactions has become a widely taken research direction. Clearly, the rise of a new generation of commercial robots capable of physical interaction has also contributed to the large interest in the field. The robotics research and industrial community expects these systems to open up new markets and to push robotics further toward domestic applications that may also involve even more complex and possibly mobile manipulators.

However, despite this recent success in research and also in the commercialization of assistance robots, there are many open research questions that need to be tackled before this class of systems can become a commodity not only in early adopter industrial applications but also on a broader scale: Continuing the road toward safe robotics by tightly coupling injury biomechanics and safe interaction control with lightweight and compliant robot design will further push the boundaries and build the foundation of pHRI. On the other hand, learning interaction controllers and planning intuitive and safe interactions are still very young fields, however, they are the key to solving the long-term physical interaction problem. Furthermore, the current application of assistance robots in real-world problems will bring further novel research questions. The recent

use of these robots clearly underlines that the programming models and paradigms of interaction and soft manipulation are very different from classical industrial robot programming. In particular, they go be-

yond simple pick and place models toward models of *force based programming*, an interesting research question currently being investigated by various researchers worldwide.

Video-References

-  VIDEO 606 Mobile robot helper – Mr. Helper
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/606>
-  VIDEO 607 Generation of human care behaviors by human-interactive robot RI-MAN
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/607>
-  VIDEO 608 Injury evaluation of human-robot impacts
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/608>
-  VIDEO 609 Safe physical human-robot collaboration
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/609>
-  VIDEO 610 Admittance control of a human centered 3 DOF robotic arm using differential elastic actuators
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/610>
-  VIDEO 611 A control strategy for human-friendly robots
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/611>
-  VIDEO 613 Human-robot interactions
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/613>
-  VIDEO 614 ISAC: A demonstration
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/614>
-  VIDEO 615 Smart fur
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/615>
-  VIDEO 616 Human-robot interaction planning
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/616>
-  VIDEO 617 The power of prediction: Robots that read intentions
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/617>
-  VIDEO 618 Reach and grasp by people with tetraplegia using a neurally controlled robotic arm
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/618>
-  VIDEO 619 An assistive decision and control architecture for force-sensitive hand-arm systems driven via human-machine interfaces (MM1)
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/619>
-  VIDEO 620 An assistive decision and control architecture for force-sensitive hand-arm systems driven via human-machine interfaces (MM2)
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/620>
-  VIDEO 621 An assistive decision-and-control architecture for force-sensitive hand-arm systems driven by human-machine interfaces (MM3)
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/621>
-  VIDEO 622 An assistive decision-and-control architecture for force-sensitive hand-arm systems driven by human-machine interfaces (MM4)
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/622>
-  VIDEO 623 Twenty One demo
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/623>
-  VIDEO 624 Full body compliant humanoid COMAN
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/624>
-  VIDEO 625 Physical human-robot interaction in imitation learning
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/625>
-  VIDEO 626 Justin: A humanoid upper body system for two-handed manipulation experiments
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/626>
-  VIDEO 627 Torque control for teaching peg in hole via physical human-robot interaction
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/627>
-  VIDEO 632 Flexible robot gripper for KUKA Light Weight Robot (LWR): Collaboration between human and robot
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/632>
-  VIDEO 716 Human-robot handover
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/716>

-  **VIDEO 717** Collaborative human-focused robotics for manufacturing
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/717>
-  **VIDEO 820** Dancing with Juliet
available from <http://handbookofrobotics.org/view-chapter/69/videodetails/820>
-  **VIDEO 821** A cobot in automobile assembly
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70. Human–Robot Augmentation

Massimo Bergamasco, Hugh Herr

The development of robotic systems capable of sharing with humans the load of heavy tasks has been one of the primary objectives in robotics research. At present, in order to fulfil such an objective, a strong interest in the robotics community is collected by the so-called wearable robots, a class of robotics systems that are worn and directly controlled by the human operator. Wearable robots, together with powered orthoses that exploit robotic components and control strategies, can represent an immediate resource also for allowing humans to restore manipulation and/or walking functionalities.

The present chapter deals with wearable robotics systems capable of providing different levels of functional and/or operational augmentation to the human beings for specific functions or tasks. Prostheses, powered orthoses, and exoskeletons are described for upper limb, lower limb, and whole body structures. State-of-the-art devices together with their functionalities and main components are presented for each class of wearable system. Critical design issues and open research aspects are reported.

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70.1 Concept and Definitions

Since early developments, one of the primary objectives of technology has been that of relieving humans from heavy tasks [70.1]. The concept of human–robot augmentation refers to the use of robotics systems to increase human functionalities in different operational contexts [70.2]. In general, the augmentation of humans' performances through the use of robotic systems refers solely to the increase in mechanical capabilities involving motion control and generation of scaled levels of forces. Although complex operations involve and exploit perceptual capabilities, in this chapter the concept of human–robot augmentation is not referred to perceptual functionalities only. Examples of working conditions in which human–robot augmentation can play an essential role for the completion of the task can be considered, e.g., operations for debris removal after an earthquake in which human operators, wearing such systems, can move and operate in a more flexible and accurate way with respect to machines like cranes or excavators.

Other scenarios are represented by tasks in which the number of repetitions, instead of level of loads to be operated, is high and becomes the critical factor for decreasing fatigue, thus maintaining long-term levels of humans' safety.

By definition, wearable robots follow the human operator's movements and in this way can inherently and fully exploit human's dexterity, thus assuring a higher level of flexibility in addressing a specific task with respect to usual loading machines. A first and fundamental characteristic, and at the same time a strict design constraint, of wearable robots is the condition of possessing a physical structure which is always in contact with the human operator's body during operation. As a consequence, wearable robots design must take into account both biomechanics and human motor control aspects.

Research on wearable robots has received a strong contribution from the development of haptic interfaces, i.e., robotic systems that are able to generate forces on the human body (force feedback) while maintaining a high level of naturalness of user's movements. The development of haptic technologies in the last two decades has focused on the importance of designing robotic systems able to generate forces at the level of the hand or other parts of the human body. As a consequence, an increased attention of the scientific robotic community toward wearable robots has been recorded. In fact, most of the recent developments on robotic

exoskeletons derive from their application in neurorehabilitation [70.3], where the robotic system is used to kinetically assist the patient's limb during the performance of specific exercises.

The augmentation of human performances can be achieved with different types of robotic systems, e.g. from teleoperated robots to self-standing robotic systems amplifying human actions. Examples of robotic systems directly operated by the human operator are the Cobot system [70.4] and the intelligent autonomous system (IAS) [70.5]. However, in the framework of the present review work, the analysis is performed by considering only robotic systems that can be worn by the user.

At present, few definitions of wearable robotic systems have been considered. Herr makes a first classification between serial and parallel system [70.6].

Serial systems are considered those that increase the length and reachability of a limb, while parallel structures contribute to the effective augmentation of torques and forces generated by the human limb. Serial systems perform their action by exploiting elastic components integrated in their structure, thus not requiring a specific computer-based control system. Other classes of wearable robotic systems can be considered the so-called *hybrid* wearable systems, i.e., parallel robotic structures worn by the human operator in which the command for their motion is achieved by FES (functional electric stimulation). In this way, the control of the robotic structure is limited and does not allow a complete force control by the user [70.7]. Hybrid systems are not considered in this chapter.

Wearable robotics systems for human augmentation can be divided into three different categories: (i) prostheses, for the functional replacement of human limbs; (ii) powered orthoses, whose function is to actively operate in parallel with unhealthy human joints; and (iii) robotic exoskeletons that operate in parallel with human limbs [70.8].

The design of the above three types of robotic systems shows different approaches whether they are referred to upper, lower limbs, or to the whole body, respectively. In the following, the analysis of wearable robotic systems is given by considering present achievements in terms of devices, robotic components utilized for the actuation, control systems architectures, and devised application domains in which they are presently utilized.

70.2 Upper Limb Wearable Systems

Upper limb exoskeletons (ULEs) are wearable robots that are placed in parallel and work in concert with the human arm. Wearer's motions that fall within ULEs coverage are shoulder elevation/depression and retraction/protraction which are provided by the human's sterno-clavicular articulation; shoulder flexion/extension, abduction/adduction and medial/lateral rotation which are provided by the human's gleno-humeral articulation; elbow flexion/extension which is provided by the human's humero-ulnar articulation; forearm prono/supination which is provided by the human's radio-ulnar articulation; wrist flexion/extension and radial/ulnar deviation which are provided by the human's radio-carpal, mid-carpal, and intra-carpal articulations; and finger abduction/adduction and flexion/extension which are provided by the human's metacarpo-phalangeal and inter-phalangeal joints.

Proposed usages of ULEs are as rehabilitation devices, motion assists, human power/force amplifiers, and haptic interfaces. Depending on the specific application, the available ULEs differ in location of placement, number of degrees of freedom (DOFs) and their subdivision between active and passive DOFs, type of kinematic architecture and implementation, type of actuators and power transmission methods, types of sensorization, and number and place of connection points between ULE and wearer.

70.2.1 Location of Placement

With regard to location of placement, a number of systems have been developed which differ from the type of segments they can cover; for instance shoulder–elbow–wrist–finger complex [70.10, 11], shoulder–elbow–finger complex [70.9] (Fig. 70.1), shoulder–elbow–



Fig. 70.1 Upper limb exoskeletons for the shoulder–elbow–wrist–finger complex (PERCRO-II, L-Exos, after [70.9])

wrist complex [70.12–16] (Fig. 70.2), shoulder–elbow–forearm complex [70.17–20] (Fig. 70.3), shoulder–elbow complex [70.21–27] (Fig. 70.4), elbow–wrist complex [70.28, 29], wrist–finger complex [70.30], and the hand (fingers only) [70.31–33].

70.2.2 Degrees of Freedom

With regard to DOFs, developed systems largely differ depending on the specific location of placement. In particular, exoskeletons with up to 9-DOFs have been developed for the shoulder–elbow–wrist–finger complex [70.16], whereas exoskeletons with up to 18-DOFs have been developed for the wrist–finger complex [70.30].

Focusing on ULEs covering at least the shoulder–elbow–forearm complex, the developed systems typically feature [70.9–13, 15–20] the following: three active DOFs for shoulder flexion/extension, abduction/adduction and medial/lateral rotation; one active DOF for elbow flexion/extension; and one DOF, either active or passive, for forearm prono/supination.



Fig. 70.2a–c Upper limb exoskeletons for the shoulder–elbow–wrist complex: (a) RUPERT (after [70.14]); (b) ARMIN (after [70.15]); (c) SUEFUL-7 (after [70.16])

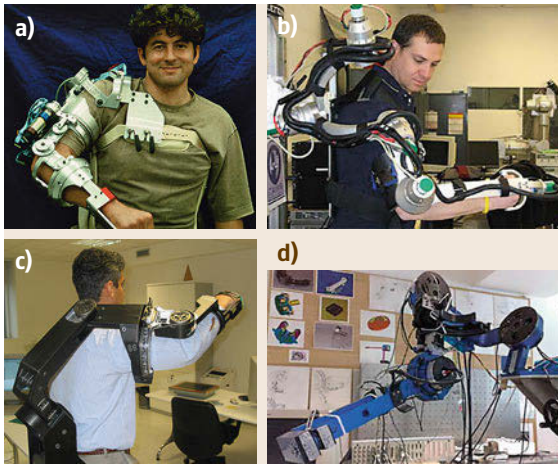


Fig.70.3a–d Upper limb exoskeletons for the shoulder–elbow–forearm complex: (a) PERCRO-I (after [70.34]); (b) MGA (after [70.19]); (c) PERCRO-III (after [70.9]); (d) RehabExos (after [70.20])

Some of these systems are also provided with a wrist having two active DOFs for flexion/extension and radial/ulnar deviation [70.10, 12, 13, 16]; an active [70.11, 15, 19, 23] or passive [70.26] DOF for shoulder elevation/depression (some systems also exist in which shoulder elevation/depression is coupled to shoulder abduction/adduction [70.15, 16, 35]); and an active [70.23] or passive [70.11, 26] DOF for shoulder retraction/protraction. Although the availability of ergonomic evaluation data is still limited, the inclusion of shoulder elevation/depression is deemed necessary for large-range-of-motion ULEs with arm elevation angles larger than 60° [70.15].

70.2.3 Kinematic Architecture and Implementation

Despite a few ULEs [70.10, 12, 26], the majority of the developed systems feature a kinematic architecture that is isomorphic to that of the wearer's upper limb (which means that the rotation axes of ULE joints are coaxial to those of the wearer's articulations). This choice usually reduces the chances of wearer–exoskeleton interference and enables the wearer to be connected to the ULE at different points over multiple links. With regard to implementation, different solutions have been proposed depending on the considered ULE articulation. In particular, three shoulder rotations have been implemented in the following different ways: (1) via three standard revolute pairs with either nonintersecting axes [70.10, 26, 26, 36] or with axes intersecting away from the center of the wearer's gleno-humeral articulation [70.12], which leads to sys-

tem designs that are not isomorphic with the wearer's limb kinematics; (2) via three standard revolute pairs with axes intersecting at the center of the wearer's gleno-humeral articulation [70.19, 23], which usually leads to ULEs with either limited range of motion or excessive encumbrance; (3) as in (2) but with the last revolute joint being a circular guide [70.9, 11, 13, 16, 20, 37], which enables for a more compact design that is, however, affected by a limited singularity-free workspace; (4) as in (2) but with the second revolute joint being a circular guide [70.38], which provides both a very compact design and a rather wide singularity-free workspace. Regarding the additional DOFs at the shoulder, both elevation/depression and retraction/protraction motions have been implemented via either revolute [70.19, 23] or prismatic [70.11, 15, 26] pairs. Elbow flexion/extension has been implemented almost univocally via a standard revolute pair. As for the wrist, flexion/extension and radial/ulnar deviation have been implemented by using two revolute joints with either intersecting axes [70.10, 12, 13] or slightly off-set axes [70.16]. In fact, in the human wrist, the radial/ulnar deviation axis passes distally with respect to the flexion/extension axis by approximately 5 mm.

70.2.4 Actuation and Power Transmission Methods

Actuation methods have also been quite variegated. Besides passive systems employing springs (or elastic bands) [70.22] and hydraulic disk brakes [70.26], ULEs have been equipped with hydraulic motors [70.10], pneumatic cylinders [70.24], pneumatic muscles [70.12, 14], and electric motors. Hydraulic motors provide very large power-to-weight ratio, high stiffness, and direct-drive operation; however, they feature low energetic efficiency and require bulky, high-pressure fluid components (power supply, valves, and tubing). Pneumatic cylinders and muscles provide large power-to-weight ratio and direct-drive operation; however they feature low energetic-efficiency, low stiffness, slow and nonlinear response, and require bulky and noisy fluid components (power supply, valves and tubing). In addition, pneumatic muscles can generate forces in one direction only, and thus they need to be used in an agonist–antagonist arrangement [70.12]. Electric motors are very efficient, easy to control, and have good power-to-weight ratio; however, they work better at high speeds. In the existing ULEs, electric motors are rarely used in direct-drive operation, but rather they are combined with either standard gearboxes (with spur [70.16] or planetary [70.9] gear-heads) or harmonic drives [70.19, 20, 27].

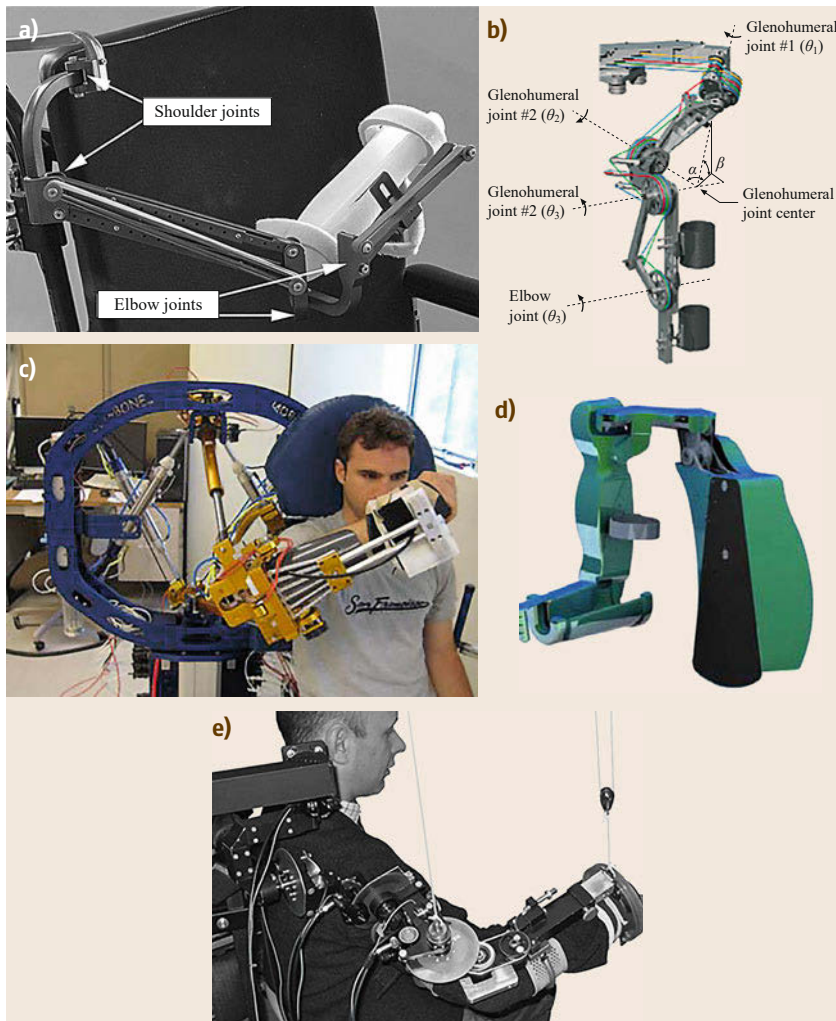


Fig.70.4a–e Upper limb exoskeletons for the shoulder–elbow complex: (a) WREX (after [70.22]); (b) MEDARM (after [70.23]); (c) BONES (after [70.24]); (d) ABLE (after [70.25]); (e) DAMPACE (after [70.26])

In the existing **ULEs**, hydraulic motors and pneumatic muscles have been located directly across single exoskeleton joints [70.10, 12, 14], whereas pneumatic cylinders have been used in an in-parallel arrangement to activate multiple joints [70.24]. Instead, electric motors have been placed either at the joints [70.19, 20] or in a remote location [70.9, 13, 23] (usually in the **ULE** base frame). This second choice has been made primarily in order to reduce the weight and inertia of moving exoskeleton parts, which enables the use of smaller motors and minimizes the disturbances on the wearer's natural motions.

ULEs with remotely placed actuators require appropriate transmission systems to transfer the power from the actuators to the joints. Except from specific cases [70.15, 23, 35] in which transmission linkages and timing belts have been used, the common

power transmission solution for **ULEs** has consisted in cable-drive systems, either closed-ended [70.9, 13] or open-ended [70.23]. Closed-ended transmissions require long cables, whereas open-ended transmissions require more motors than the number of actuated **DOFs**. Both open- and closed-ended cable-drive systems are lightweight, highly efficient, and back-drivable; thus they are very good solutions to transmit mechanical power over long distances. In addition, cable drives enable the easy implementation of speed-reduction stages, which should be placed as close as possible to the joint in order to maximize overall transmission stiffness [70.9]. Moreover, cable-drive transmissions spanning multiple joints make it possible to distribute loads across several cables, which can be used to minimize the torque requirements of the actuators [70.23].

70.2.5 Type of Sensorization

Apart from few passive systems only conceived as weight compensation devices [70.39], all the developed **ULEs** are equipped with position sensors (potentiometers or encoders), which are placed at the motors and/or at the joints so as to make it possible to estimate/control the overall system configuration. Besides, the considered **ULEs** largely differ from the point of view of force/torque sensorization. Thanks to the intrinsic low friction and high back-drivability, exoskeletons with cable-drives have been designed to operate without the need of force/torque sensors [70.9, 13, 23]. All the other **ULEs** are instead equipped with this kind of sensorization, which can be either concentrated at the points of connection with the wearer [70.11, 15, 16, 19] or distributed at every **ULE** joint [70.20]. The use of torque sensors distributed at every **ULE** joint enables for multicontact force control at multiple points distributed over multiple links and, additionally, makes it possible to design very robust force-feedback controllers that are rather insensitive to exoskeleton link variable inertia, transmission compliance, friction losses, actuator torque ripples, and gear teeth wedging actions [70.20]. The use of multi-DOF force/torque sensors concentrated at the points of wearer-**ULE** interaction makes the use of the exoskeleton less flexible and the controller less robust, but enables for a more accurate estimation and control of the endpoint forces that are exchanged with the wearer. In general, **ULEs** equipped with force/torque sensorization provide better haptic feedback than those relying on cable-drive transmissions only.

70.2.6 Hand Exoskeletons

The functionality of hand exoskeletons (**HE**) consists in exerting programmable forces on human fingers. Hand exoskeletons can be classified in two functional categories depending on the capability of exerting forces on a single phalanx (usually the distal phalanx correspondent to the fingertip) or on multiple phalanges (Fig. 70.5).

Multiphalanx hand exoskeletons (**MPHE**) are devices able to exert different forces on at least two of the phalanges of the same finger: usually the force can be applied on a fixed direction normal to the phalanx axis and belonging to the medial plane of the finger.

Single-phalanx hand exoskeletons (**SPHE**) are able to exert forces on one phalanx of the finger, usually the distal one only; some devices are able to generate a force only along a fixed direction but more commonly they can exert forces with any desired orientation.

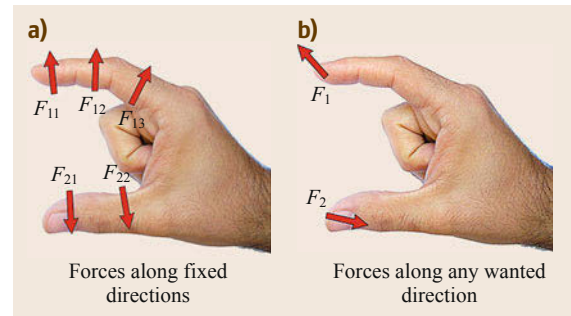


Fig. 70.5 (a) Multiphalanx and (b) single-phalanx scheme for hand exoskeletons

Another taxonomy of hand exoskeletons considers two other categories:

- Anthropomorphic devices: the kinematics of the **HE** is morphologically similar to the human fingers
- Nonanthropomorphic devices: the kinematics is morphologically different from the human fingers.

The scientific literature in the last 30 years reports many works dealing with different **HE** designs mainly addressing three application fields: (1) teleoperation and virtual environments in which the **HE** are utilized as master controllers providing force feedback or for generating illusory forces to the hand of the human operator; (2) neurorehabilitation, in which **HE** are used for restoring hand functionalities after strokes or other neural impairments; (3) space applications in which **HE** are employed as active devices for extending grasping forces of the astronauts in extra vehicular activities.

The first known example of **HE** was introduced in the field of teleoperation by *Zarudiansky* back in 1981 [70.40]. The inventor has registered a patent for a tele-manipulation system equipped with a master device able to provide force feedback on different phalanges of the human hand. At the Jet Propulsion Laboratory Pasadena (**JPL**) in 1988, *Jau* [70.41] built a complete teleoperated master/slave system comprehending a hand exoskeleton device for four fingers. In the same years *Burdea* et al. developed a pneumatic actuated hand force feedback device [70.42], called Rutgers Master, able to exert a single force to the distal phalanx along a direction dependent on the kinematics of the device and on the position of the finger. *Bergamasco* [70.37] developed a four-finger **MPHE**. A nonanthropomorphic device was realized by *Koyama* et al. at Keyo University; this device is a three-finger exoskeleton for thumb, index, and middle finger with passive clutches actuation [70.43]. Such a device is anchored at the user's wrist and is able to exert forces in every direction belonging to the sagittal plane

of the fingers. *Frisoli et al.* [70.9] developed another nonanthropomorphic **HE**, called Pure Form Hand-Exos for virtual environment (**VE**) applications that features a very complex steel cable transmission studied for an optimal use of motor torque. *Nakagawara et al.* [70.44] built a device integrating the concept of encountered haptics: the device possesses 1-**DOF** for each finger and it is able to track the finger without any contact (even at the fingertip) through a noncontact sensor placed in correspondence of the nail. When contact is detected in the remote/virtual environment, a plate is moved against the user's fingertip. Another example of anthropomorphic hand exoskeleton for **VE** applications has been developed by *Fontana et al.* [70.32] with the aim of maximizing force accuracy and resolution (Fig. 70.6).

Other examples of **HEs** have been developed for medical applications. In this field, **HEs** are employed for rehabilitation procedures or as power-assisting devices (orthoses). In rehabilitation procedures a **HE** is commonly used for exerting forces (or trajectories) and, at the same time, measuring velocities and positions (or force) of the fingers. *Gomez et al.* [70.45] have integrated the Rutgers Master in a **VE** rehabilitation system. *Wege et al.* [70.46] developed a 4-**DOF HE** with a modular structure, actuated by Bowden cables. *Mulas et al.* [70.47] realize a **HE** that makes use of electromyography (**EMG**) signals for predicting the movements of the user finger. *Ito et al.* [70.48] built a complex **HE** for rehabilitation purposes with 4-**DOF** for the index, medium, and ring fingers and 5-**DOF** for the thumb, able to exert controlled torque on each phalanx.

HEs can implement the functionality of supporting people with permanent disabilities to perform common activities for daily living (**ADL**). Such devices, called hand orthoses or assistive **HE**, are controlled as power extenders allowing the user to exert only a fraction of the force required to accomplish the task. The first orthosis for the finger was developed by *Brown et al.* [70.49]. The realized device was a **HE** composed by three rings attached on the phalanges that were actuated with pulling cables. Other examples of hand orthoses are described in [70.4, 39]. Another field where **HEs** have proved their usefulness is in assisting astronauts in performing **EVA** (extra-vehicular activities). Due to the pressure difference, the suits that the astronauts wear during **EVA** require high force to be bended and represent a major constraint especially for manipulative tasks. For this reason, custom-designed **HEs**

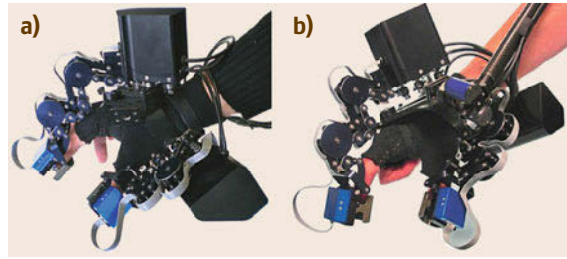


Fig.70.6a,b Hand exoskeleton (after [70.32]) (a) without and (b) with tracking system

are used as an active tool to overcome the stiffness of the gloves. *Shields et al.* [70.50] developed the first **HE** for space applications. Such a device was an anthropomorphic **HE** with three active fingers; the thumb was excluded and the little finger was connected together with the ring finger. The **HE** has two **DOFs** for each finger and exploits a special mechanisms for the implementation of the finger flexion joints. The anthropomorphic kinematics is obtained through remote center of rotation joints. In 2001, *Yamada et al.* [70.51] developed, for the same space applications, another simplified **HE** called Skill Mate in which only the first flexion **DOF** of each finger is actuated. The **HE** developed by *Wang et al.* [70.52] is still utilized for the simulation and evaluation of different space gloves. The device features a kinematics implementation that is close to the **HE** developed by Shields but in this case the device has three **DOFs** coupled in a way that only one actuator is needed for each finger. Also in this case, flexion joints are implemented through remote center of rotations allowing the **HE** joints to closely correspond with the natural joints (metacarpophalangeal **MCP**, interphalangeal **IP**, distal **D**) of the human hand.

In general, it can be observed that **HEs** realized for **VE** and teleoperation have several mechanical features that are not present in the devices conceived for rehabilitation, **ADL** or **EVA** applications. **VE** and teleoperation application require in fact the simulation of fine haptic interaction and generally more demanding performances are needed in terms of mechanical features. In **VE** and teleoperation, the design of **HE** requires to minimize friction, inertia, and weight. On the other side, in other applications, a higher level of friction can be tolerated, allowing the use of Bowden cables for delocalizing the motors, or a simplified kinematic structure can be acceptable allowing exerting forces with less accuracy.

70.3 Lower Limb Wearable Systems

Lower extremity autonomous wearable robotics is a general classification covering actuated leg prostheses, orthoses, and exoskeletons.

70.3.1 Lower Extremity Autonomous Wearable Robotics

These robots are defined as active mechanical devices that are worn on a wearer's legs, and work in concert with the wearer's movements, either as permanent assistive devices for persons suffering from leg pathology, or augmentative devices for persons having *normal* physiological leg function. In general, the classification *active leg orthosis* is typically used to describe a device that is used to increase the capacity of a person suffering from leg pathology to ambulate, whereas the classification *leg exoskeleton* is used to describe a device that augments the locomotory performance of an able-bodied wearer. However, the classification *leg exoskeleton* has also been used to describe certain assistive devices that span in parallel across the entirety of the human leg [70.6]. Autonomous wearable leg robots are used as assistive interventions in the treatment of leg disabilities caused by amputation, stroke, cerebral palsy, and multiple sclerosis. In the realm of human augmentation, leg exoskeletons have been constructed for load-carrying augmentation, to improve the economy of walking or running, or to decrease musculoskeletal stress [70.6].

Since robots within this classification are worn by the wearer, it is critical that their design resemble biological leg function, both morphologically and neurologically. For this discussion on lower extremity wearable robotics, we use the term *bionic* to refer to an electromechanical structure designed to emulate, or extend, normal physiological function. A long-standing goal in robotic science is to apply neuromechanical principles of human movement to the development of highly functional wearable leg robotics [70.53]. Critical to this effort is the development of actuator technologies that behave like muscle, device architectures that resemble the body's own musculoskeletal leg design, and control methodologies that exploit principles of biological leg movement. In the next section, we present a computational model of human walking that unifies muscle and joint biomechanics with whole-body metabolism for level-ground walking at self-selected speed. The model underscores critical design principles for wearable leg robotics, including the importance of tendon-like compliance and reflexive control on locomotory performance – discussed in detail in Sect. 70.3.6. These design principles are discussed in

detail and then, by way of example, used to analyze the design of a bionic transtibial prosthesis. The chapter concludes with a discussion on critical areas for future research.

70.3.2 Neuromechanical Basis for Wearable-Robotic Leg Design

By understanding the underlying mechanisms that govern individual muscle–tendon behaviors in human locomotory function, roboticists can better design wearable robots that seamlessly integrate dynamically with the biological leg. To this end, in this section we present a computational model of human walking [70.54] that unifies muscle and joint biomechanics with whole-body metabolism for level-ground walking at self-selected speed. The model, shown in Fig. 70.7, comprises ankle, knee, and hip joints connected by rigid bodies representing the human trunk and two, three-segment legs. In the model, muscle–tendon units that dorsiflex the ankle, and flex and extend the knee, are assumed to act as linear springs upon neural activation; each muscle–tendon is modeled as a tendon spring in series with an isometric force source, or a controllable clutch. To provide the mechanical power for step-to-step gait transitions, a Hill-type soleus muscle is modeled to actively plantar flex the ankle throughout mid to terminal stance using muscle state and force as reflex feedback signals. Finally, to stabilize the trunk during stance, and to protract and retract each leg throughout the swing phase, two mono-articular Hill-type muscles actuate the model's hip joint. State transitions of a finite machine were facilitated by the walking model, and its interactions with a modeled ground surface, and each muscle was engaged or activated according to state [70.54]. Following a forward dynamic optimization procedure described in [70.54], the walking model is shown to predict joint biomechanics, as well as whole-body metabolism, as shown in Fig. 70.8, supporting the idea that the preponderance of leg muscle–tendons operates isometrically, affording the relatively high metabolic walking economy of humans.

70.3.3 Design Principles for Wearable Leg Robotics

Neuromechanical models of human locomotory function such as the *Endo* and *Herr* model [70.54] provide critical insights into wearable robotic leg design. Biophysical models that describe the morphology and neural control of human limbs can motivate robotic designs that are quiet, low mass, economical, and stable;

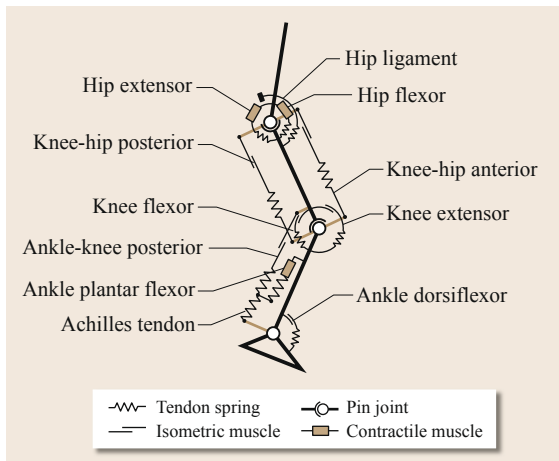


Fig. 70.7 The musculoskeletal walking model of Endo and Herr [70.54]. Only three contractile muscles act about the model's ankle and hip joints capable of performing nonconservative positive work, namely the ankle plantar flexor, representing the soleus muscle, and two mono-articular, hip flexor/extensor muscles. All remaining muscle–tendon units of the leg are modeled as an isometric muscle in series with a compliant linear tendon spring. The hip joint also includes a unidirectional, linear torsional spring representing the dominant ligaments that tend to flex that joint

robots that move like, and feel like, their biological counterparts. In the subsequent sections, we discuss key design features critical for a robotic prosthetic, orthotic, or exoskeletal leg to behave like a healthy, normal biological leg. Each design principle is first discussed, and then applied to a leg prosthesis for a transtibial amputee.

70.3.4 Series and Parallel-Elastic Actuation for Power Amplification

Perhaps the most paramount design feature of a wearable robotic leg is a biomimetic actuator architecture designed to achieve biologic levels of powered plantar flexion at the ankle during terminal stance. The biological calf muscles generate nearly 80% of the mechanical work required to complete each gait cycle during mid to late stance plantar flexion, and typically performs greater positive than negative ankle work during each stance period of level-ground walking [70.36, 56–61]. Ankle-powered plantar flexion in the trailing leg is critical for powering the transition from one single support phase to the next single support phase, minimizing impact of the leading leg [70.56, 58]. For this purpose, in the walking model of [70.54] shown in Fig. 70.7, a Hill-type soleus muscle, or ankle plantar flexor, is

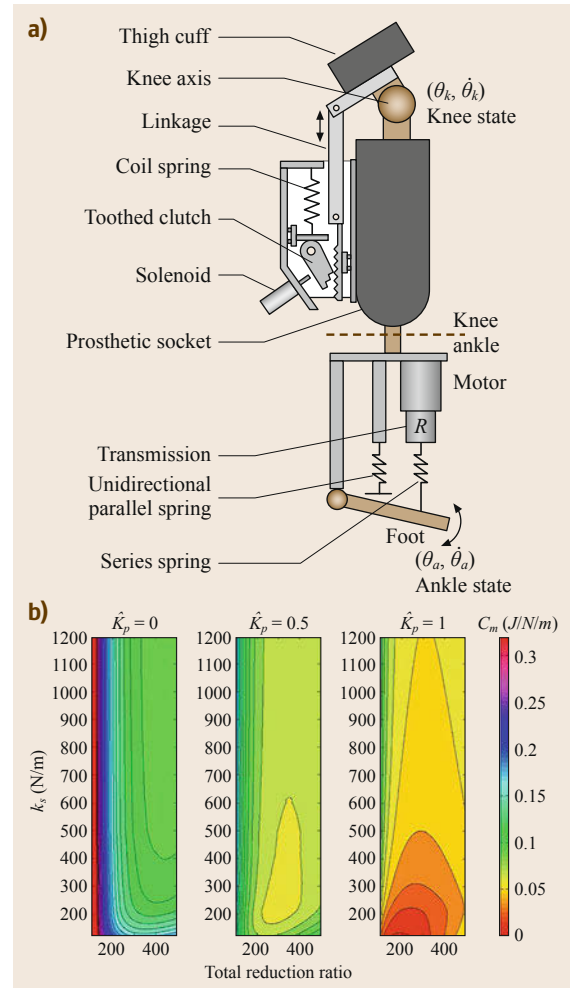


Fig. 70.8 Biomechanical and energetic predictions from the walking model shown in Fig. 70.7. Plotted is the maximum cross-correlation coefficient R , summed across three joint angles and normalized by 3, versus the metabolic cost of transport (COT), or the metabolic energy required to transport unit body weight unit distance. $R = 1$ indicates perfect agreement with biological ankle, knee and hip angle data throughout one gait cycle, whereas $R = 0$ indicates no agreement. Each closed circle is one forward dynamic model solution that can walk for at least 20 s without falling down. The dashed line and shaded area represent mean $\pm$ one standard deviation for human metabolic COT data from the literature [70.55]. The open diamond is the model's optimal solution with a maximal R value, and energetically within one standard deviation of the average human walking metabolism

modeled to actively plantar flex the model's ankle from mid to late stance. The muscle is in series with a tendon spring, representing the Achilles tendon. Further, the

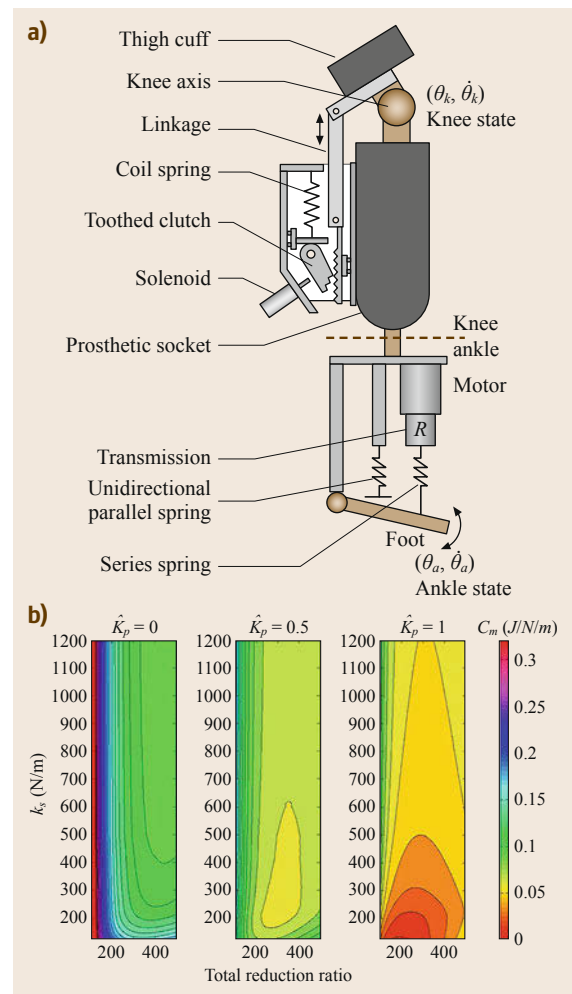
bi-articular gastrocnemius muscle, or the ankle–knee posterior in Fig. 70.7, spanning the ankle and knee, is modeled as an isometric force source, or clutch, in series with a tendon spring.

Such an architecture is critical for powering ankle plantar flexion while still achieving efficient, low-mass robotic actuation. Since the ankle–knee posterior muscle in Fig. 70.7 is shown to transfer little mechanical energy between the knee and ankle throughout the walking gait cycle [70.54], it is reasonable to model this muscle using mono-articular actuators about the knee and ankle. In such a framework, the effect of the ankle–knee posterior on these joints is represented as effective monoarticular torque-producing elements. Such an architecture is shown in Fig. 70.9a showing the schematic of a bionic transtibial prosthesis. Here the ankle is modeled as a series-elastic actuator (SEA) in parallel with a unidirectional parallel spring. The SEA represents the ankle-plantar flexor in Fig. 70.7, and the unidirectional spring represents the torque contribution of the ankle–knee posterior muscle on the ankle joint.

In Fig. 70.9b, the results of a compliant transmission optimization are presented, showing the effects of ankle total reduction ratio, series stiffness, and parallel stiffness on the ankle prosthesis COT. The prosthesis COT is equal to the amount of electrical energy consumed by the prosthesis throughout one gait cycle, divided by the product of half body weight and the distance traveled in one gait cycle. The half body weight in the denominator assumes that each transtibial prosthe-

sis has its own power supply. Without parallel stiffness ($\hat{K}_p = 0$), the energy consumption of the prosthesis is minimal at a total reduction ratio greater than 400, and a series spring stiffness greater than 400 kN m^{-1} . As parallel spring stiffness increases ($\hat{K}_p > 0$), the prosthesis COT can attain a lower minimum value while also requiring a smaller total reduction ratio and series spring stiffness. Using a lower reduction ratio allows the system to have a larger bandwidth, a faster intermittent response, and a lower acoustic noise output. Further, a lower series stiffness improves the prosthesis COT as shown in Fig. 70.9a, shock tolerance upon impact loading at heel-strike [70.62], and motor power amplification at the ankle joint output [70.63]. For further details on compliant ankle transmission design, see [70.62, 63]. In the design of bionic ankle–foot wearable robots, both motor-series and parallel elasticity are of paramount importance.

Fig. 70.9a,b Shown in (a) is a bionic transtibial prosthesis represented as an electromechanical schematic including ankle motor, ankle transmission ratio R , ankle series spring k_s , and ankle unidirectional parallel spring k_p . The parallel spring is unidirectional, engaging only at ankle angles less than 90° but completely disengaged for angles greater than 90° . In addition, spanning the knee joint are elements of a series-elastic clutch mechanism. Plotted in (b) are the results of a compliant ankle transmission optimization showing the effects of ankle reduction ratio, series stiffness k_s and normalized unidirectional parallel stiffness $\hat{K}_p$ on ankle prosthesis cost of transport, C_m . Parallel stiffness, normalized by the human-controlled dorsiflexion stiffness of 630 Nm rad^{-1} is noted as $\hat{K}_p$ on the upper portion of each graph. The total reduction ratio is equal to the SEA moment arm r multiplied by transmission ratio R . The compliant ankle assembly shown in (a) was constrained to track biological ankle torque for a human subject with a mass of 78 kg walking at 1.25 m s^{-1} with a stride distance of 1.4 m . Further details of the compliant transmission optimization can be found in [70.62]. ►



70.3.5 Series-Elastic Actuation for Minimizing Motor Work

It has been hypothesized that the preponderance of leg muscle–tendons generates force at low muscle fascicle speed, allowing economical force generation in level-ground walking [70.54]. In the walking model shown in Fig. 70.7, six of the nine leg muscles act in a purely isometric manner, where a tuned, series-tendon compliance enables full energy absorption and delivery, eliminating muscle work and lowering metabolic demands in walking. Specifically, all muscles spanning the knee, as well as the ankle dorsiflexor, are assumed to act isometrically upon neural activation when ambulating across a level-ground surface.

For wearable robotic actuation in level-ground walking, such behaviors can be achieved using a series-elastic clutch mechanism with a tuned series stiffness. However, for a more diverse set of locomotory tasks such as ascending and descending slopes and steps, the ideal actuator architecture is a series-elastic actuator with a tuned series-spring stiffness where the actuator is designed to lock or clutch at lower power consumption. As an example, for level-ground ambulation using an electric actuator, a clutch acting on the motor shaft can be used to lock the shaft during those times in the gait cycle where a spring response is sought, eliminating the high power consumption required if the motor itself were to clutch the shaft. For other movement tasks outside of level-ground walking, the motor–shaft clutch could then be disengaged, and the motor could apply the necessary torques and impedances required for the task using standard series-elastic actuation strategies [70.64]. Such an architecture allows wearable robotic legs to move economically across level-ground surfaces, while still allowing a great deal of versatility for irregular-ground ambulation, sit-to-stand maneuvers, and general disturbance rejections.

This design principle of using a tuned series stiffness to minimize the need for actuator work has been used in the design of a transtibial prosthesis in [70.65] (Fig. 70.9a). Since the gastrocnemius was modeled in [70.54] as an isometric force source in series with a tendon spring, in the study of [70.65] a series-elastic clutch was mounted at the knee brace to provide the knee flexion action of the gastrocnemius during level-ground walking. The mechanism consisted of a toothed clutch at the free end of a coil spring (spring stiffness of 66 500 N/m) that acted as a knee flexor on a polycentric knee brace. The brace was integrated into a prosthetic socket connected to the ankle–foot prosthesis, as is shown in Fig. 70.9a. When the clutch was engaged via solenoid action, the free end of the spring locked with respect to the socket and the spring stretched as the

knee straightened. The force developed by the spring produced a flexion torque at the knee joint. Conversely, when the clutch disengaged no torque was applied at the knee joint. The spring acted on the knee joint with a moment arm that varied between 0.02 and 0.03 m as a function of knee angle. This moment-arm function was designed so that the apparent knee stiffness matched that of the biological knee during level-ground walking [70.66].

70.3.6 Neuromuscular-Based Reflexive Control

We present a sensing and control scheme for producing biomimetic positions, torques and impedances at the hip, knee, and ankle joints of a powered leg prosthesis, orthosis, or exoskeleton during walking and running gaits. In this paradigm, sensory data are collected using intrinsic and/or extrinsic sensors. Here intrinsic sensing refers to information collected from sensors located on the wearable robotic device, and extrinsic sensing refers to all information collected from sensors located externally to the wearable device. As an example, in the case of a leg prosthesis, a surface electrode for the measurement of the electromyographic signal from residual limb muscles would be an extrinsic sensor, and an inertial measurement unit located on the device itself would be classified as an intrinsic sensor. Intrinsic sensors measure device positions, motions, forces, torques, pressures, and temperatures, whereas extrinsic sensors might comprise such mechanical and temperature sensors positioned external to the wearable device, as well as neural sensors for the determination of user motor intent.

In the neuromuscular-based control framework, such sensory data are passed to a neuromuscular model of human locomotion, such as the *Endo* and *Herr* model [70.54] presented in Fig. 70.7, which is used to compute appropriate joint dynamics for the device to provide to the user. The model-based control scheme, depicted in Fig. 70.10, relies on data collected from both intrinsic and extrinsic mechanical sensors, and extrinsic neural sensors used to infer the motor intent of the user, volitionally and/or nonvolitionally. The neuromuscular model used to compute desired joint dynamics may include muscles modeled in a variety of ways. These muscle models (muscle model block in Fig. 70.10) may include, for example, a bilinear muscle model or a Hill-type muscle model [70.67]. The measured states of the robotic joints are used to determine the internal state (length, velocity) of each of the virtual muscle–tendon units of the neuromuscular model using morphological information of the muscle moment arms about each modeled joint. This geometrical transforma-

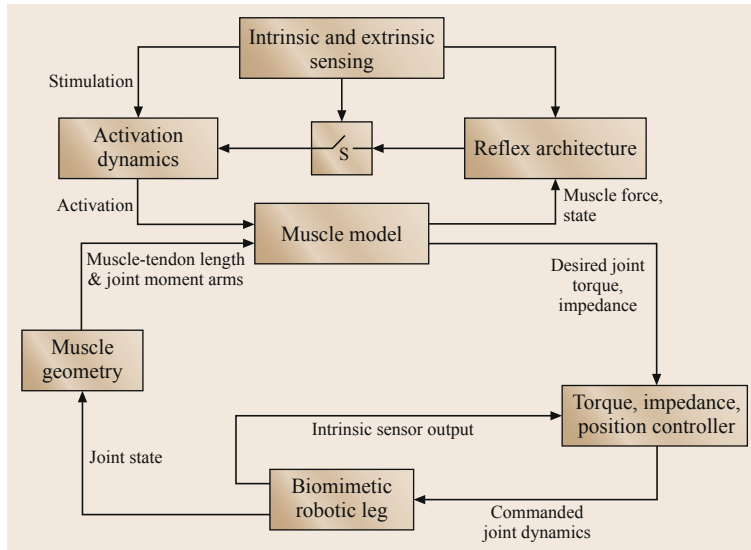


Fig. 70.10 Block diagram of a neuromuscular model-based control architecture for a bionic wearable robotic leg

tion occurs within the muscle geometry block shown in Fig. 70.10.

The impedance and force of each virtual muscle are additionally governed by the muscle activation, which may be determined from a local reflex loop, an external source, or a combination thereof. In the reflex case, a feedback loop is implemented where virtual muscle force and state are used to produce muscle stimulation, which is then filtered to produce muscle activation (activation dynamics block in Fig. 70.10). This feedback-based control scheme is designed to emulate the force feedback and stretch reflex of an intact human muscle. This reflexive feedback loop can be a linear or nonlinear function of virtual muscle force, length, and velocity. For example, the reflexive feedback loop can be nonlinear, comprising a threshold prestim parameter, as well as force and state gains and exponents, or

$$u(t) = x + y_F [F(t - \Delta t_F)]^{z_F} + y_L [l(t - \Delta t_L)]^{z_L} + y_v [v(t - \Delta t_v)]^{z_v}, \quad (70.1)$$

where x is the prestim parameter, y_i are force and state gains, z_i are force and state exponents, and t_i are corresponding delays.

In the case where muscle activation is determined solely by an external source, a neural sensor might be used to provide some estimate of motor intent, which is then input to the activation dynamics block where a muscle activation is estimated as an input to the muscle model. Typically, such measurements of motor intent would comprise one or more peripheral neural sensors from implants interfacing with nerves and/or

muscles, but in the most general case, such motor intent commands may additionally be measured from central brain implants.

In the combination case, the framework of Fig. 70.10 describes a procedure where the reflexive parameters are modulated by the controller either within a single gait cycle, and/or from gait cycle to gait cycle in an updating manner, based upon detected variations in gait speed and terrain. Extrinsic efferent neural signals from muscles and/or peripheral nerves might be used to modulate reflexive parameters, such as force and state gains and exponents. For example, measured calf muscle EMG in a transtibial amputee has been used to modulate the gain of a positive torque feedback during the stance period of a walking gait cycle, providing the amputee direct volitional control over powered plantar flexion during terminal stance in walking [70.68]. Clearly, one day it may be possible to stimulate through a nerve implant to reflect intrinsic/extrinsic mechanical sensory data as an afferent feedback signal to allow the user of the wearable robot to better modulate efferent neural motor commands for a desired wearable robotic dynamical response.

Once the force of each virtual muscle spanning a joint is determined (using the implemented muscle model), each muscle force is multiplied by its biologically realistic muscle moment arm and then all muscle torque contributions are summed around the joint to produce a net torque and impedance estimate. The model estimates are then sent to the controller (Fig. 70.10) as the desired net torque and impedance for each robotic joint. The controller tracks these desired values at each joint to produce human-like joint forces and impedances. In the case where the human

user's motor intent is to control device joint position, the controller would integrate the desired joint torque to achieve a joint position estimate, and then modulate device joint position to achieve that desired position.

By way of example, we present a neuromuscular-based control of a transtibial prosthesis (Fig. 70.11). For this example, the model-based control framework of Fig. 70.10 is used to control the prosthetic apparatus. In the study of [70.65], ankle and knee joint states of the apparatus were measured and used to provide real-time input to a neuromuscular model simulated by an on-board microcontroller. The resulting torque command from the neuromuscular model was used to produce ankle torque while a knee controller adjusted the torque produced by the knee brace. This configuration, shown in Fig. 70.11, was set up to enable the prosthetic apparatus to behave as if it were a human lower leg with reflex-controlled muscles acting at the ankle (Fig. 70.12).

70.3.7 Leg Exoskeletons

Research has lead to the development of leg exoskeletons with the prime intention to allow otherwise healthy individuals to perform difficult tasks more easily or

enable them to perform tasks that are otherwise impossible using purely human strength or skill [70.69]. Early developments in leg exoskeletons consisted of long bow/leaf springs operating in parallel to the legs and were intended to augment running and jumping [70.70]. Each leg spring was engaged during the foot contact to effectively transfer the body's weight to the ground and to reduce the forces borne by the stance leg. During the aerial phase, the parallel leg spring was designed to disengage in order to allow the biological leg to freely flex and to enable the foot to clear the ground. In 1963, Zarodny published a technical report detailing his work on a *powered orthopedic supplement* intended to augment the load-carrying abilities of an able-bodied wearer such as a soldier [70.71]. Other early implementations of exoskeletons, including legs, were attempted by General Electric Research with the *Hardiman* project [70.72], by Moore at the Los Alamos National Laboratory, and *Rosheim* [70.73]. However, a major impetus for the recent work in performance augmenting exoskeletons has come from the **DARPA** (Defense Advanced Research Projects Agency) program *Exoskeletons for Human Performance Augmentation (EHPA)* [70.74], the outcomes of which were different working exoskeletons.

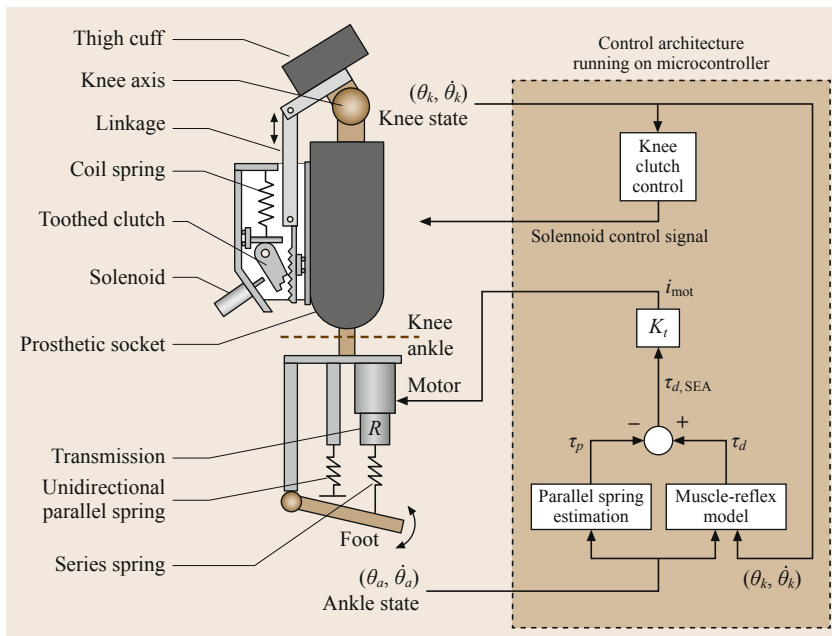


Fig. 70.11 Labeled schematic and control architecture for the prosthetic apparatus. Rotary elements in the ankle-foot prosthesis are shown as linear equivalents in the model schematic to improve clarity. In the control schematic, the parallel spring contribution to prosthesis ankle torque, τ_p , was subtracted from the desired ankle torque command from the neuromuscular model, τ_d , to obtain the desired SEA torque, $\tau_{d,SEA}$. A motor current command i_{mot} was obtained by dividing the desired SEA torque by the motor torque constant, K_t . The knee clutch was engaged via the solenoid depending on knee state as obtained from the knee potentiometer. For further details on the mechatronic and control design, see [70.65]

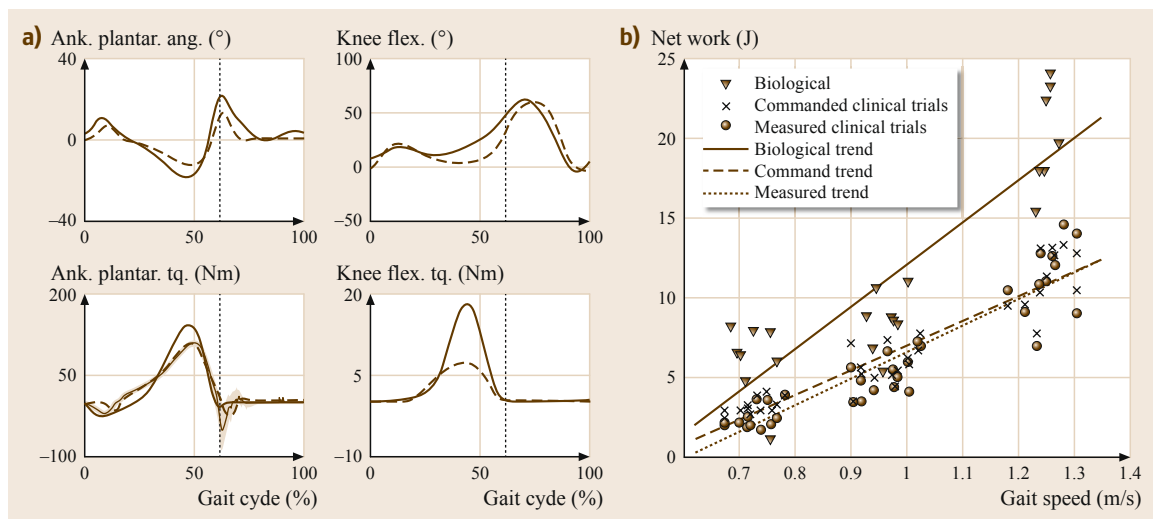


Fig. 70.12 (a) Comparison of prosthesis ankle and knee angles and torques during the clinical trials (measured) with those from a height- and weight-matched subject with intact limbs (biological). The biological values are the thick solid lines (with shaded errors) in each plot while the dashed lines are the values measured on the prosthesis. In the ankle torque plot the commanded torque is shown as a thinner solid line, again with shaded error bars. The knee torque plot compares the torque provided by the clutch-spring mechanism to that provided by the natural gastrocnemius in simulation. The vertical line indicates toe-off in each plot. **(b)** Energy output of the ankle across gait speed. Shown are biological data, net work as commanded by the ankle-foot prosthesis during clinical trials, and measured net work during the clinical trials. For further details on experimental methodology and results, see [70.65]

In this framework, the Berkely Exoskeleton (BLEEX) was the first example of an energetically autonomous system [70.75]. BLEEX features 3-DOF at the hip, 1 at the knee, and 3 at the ankle. Of these, four are actuated: hip flexion/extension, hip abduction/adduction, knee flexion/extension, and ankle inversion/eversion. Of the unactuated joints, the ankle inversion/eversion and hip rotation joints are spring loaded, and the ankle rotation joint is free-spinning [70.76]. The BLEEX exoskeleton [70.77] was designed with linear hydraulic actuators since they were the *smallest actuation option available* based on their *high specific power (ratio of actuator power to actuator weight)* [70.78, 79]. However, a further study determined that electric motor actuation significantly decreased power consumption during level walking in comparison to hydraulic actuators [70.80, 81]. The weight of the implementation of the electrically actuated joint, however, was approximately twice that of their hydraulically actuated joint (4.1 versus 2.1 kg). Significant effort was made in developing a hybrid hydraulic-electric portable power supply [70.82]. In terms of performance, users wearing BLEEX can reportedly support a load of up to 75 kg while walking at 0.9 m/s and can walk at speeds of up to 1.3 m/s without the load. A second generation of the Berkeley exoskeleton is currently in testing. A laboratory spin-off company called Berkeley Bion-

ics (Berkeley, CA) has been created in order to market exoskeleton technology.

A quasi-passive exoskeleton concept has been advanced in the Biomechatronics Group at the Massachusetts Institute of Technology (MIT) Media Laboratory that seeks to exploit the passive dynamics of human walking in order to create lighter and more efficient exoskeleton devices. The MIT exoskeleton employs a quasi-passive design that does not use any actuators for adding power at the joints. Instead, the design relies completely on the controlled release of energy stored in springs during the (negative power) phases of the walking gait [70.83]. The 3-DOF hip employs a spring loaded joint in the flexion/extension direction that stores energy during extension that is released during flexion. The hip abduction/adduction direction is also spring loaded, but only to counter the moment induced by the backpack load. Additionally, a cam mechanism was incorporated into the hip to compensate for the relative change in length between the thigh of the exoskeleton and the user due to the joint offset during abduction/adduction. Additionally, spring loaded hip rotation and ankle rotation joints were included to allow nonsagittal plane limb movements. The knee of the MIT exoskeleton consists of a magneto-rheological variable damper that is controlled to dissipate energy at appropriate levels throughout the gait cycle. For the

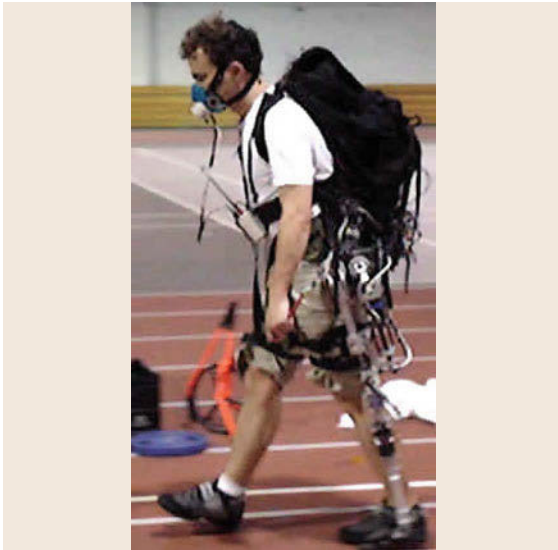


Fig. 70.13 MIT exoskeleton during metabolic testing

ankle, separate springs for dorsi and plantar flexion are implemented in order to capture different behaviors during these two stages of motion, and store/release the optimum amount of energy. Without a payload, the exoskeleton weighs 11.7 kg and requires only 2 W of electrical power during loaded walking. This power is used mainly to control the variable damper at the knee. The first studies on the metabolic cost associated with walking under the aid of an exoskeleton have been reported by using the MIT exoskeleton [70.84] (Fig. 70.13).

Further experimental work with the MIT quasi-passive exoskeleton showed a significant reduction in metabolic cost of walking versus the same exoskeleton without the springs at the hip and ankle and the variable damper at the knee, demonstrating the utility of quasi-passive elements.

Other examples of leg exoskeletons comprehend the hybrid assistive leg developed at the University of Tsukuba by Sankai [70.85] that is targeted for both performance-augmenting and rehabilitative purposes. At the Kanagawa Institute of Technology in Japan, researchers have developed an exoskeleton for the purpose of assisting nurses during patient transfer [70.86]. Yobotics, Inc. (Cincinnati, OH) [70.87] developed a simple exoskeleton for adding power at the knee to assist in stair climbing and squatting during load-carrying tasks [70.78]. Researchers in the Departments of Mechanical Engineering and Physical Therapy at the University of Delaware have developed a passive leg orthosis that is designed to reduce the forces of gravity on the patient during walking, thus easing the effort required for locomotion [70.88]. Caldwell has developed a 10-DOF lower limb exoskeleton device [70.81]: actuation is provided to the flexion/extension directions of the hip, knee, and ankle, and abduction/adduction of the hip via pneumatic muscle actuators. Recently, few leg exoskeleton systems have been commercialized worldwide by different companies: the ReWalk lower limb exoskeleton developed by Argo Medical Technologies, Israel [70.89] for elderly/paraplegic assistance, and the system called REX developed by Rex Bionics, New Zealand [70.90].

70.4 Whole Body Wearable Systems

Despite the considerable interest and impressive advancements in the field, so far only few researchers have attempted the development of full-body EHPA (FB-EHPA), in particular fully actuated systems for heavy-duty applications, and the available scientific literature is quite limited [70.8, 83, 85, 91–99]. This section reviews the general design issues concerning electro-mechanical design of FB-EHPA. The general design issues are analyzed considering and presenting a series of specific designs.

70.4.1 General Issues

Kinematic Architecture

The kinematic scheme of FB-EHPA is a fundamental aspect that strongly affects the basic functionalities and capabilities of such machines. Just as other wearable

robots, the kinematic design is strongly influenced by the close proximity of robot linkages and human limbs. Kinematics of an FB-EHPA must be designed in order to be compatible with:

- The execution of common human movements: walking, squatting, lifting, turning, etc.
- Requirements for the execution of specific tasks: raising weights, handling specifically shaped objects, running, etc.
- Encumbrance and spatial limitation
- Possible collisions with the operator body and self-interferences.

Common solutions for the existing FB-EHPA are based on anthropomorphic kinematics since this kind of solution guarantees:

- The best workspace matching with reduced encumbrances
- The most simple strategy to avoid self/body collisions
- The execution of common human movements
- Mass distribution that is compatible with human executed tasks.

A full anthropomorphic design that allows replicating all the human [DOFs](#) could be desirable; however, the complexity of such a system would be far above what is technically affordable. In this sense, a drastic simplification is required to reduce complexity without affecting the basic functional requirements of the machine. This type of simplification is assumed in many of the available [FB-EHPA](#).

70.4.2 Specific Design

According to a historical perspective, the first technical concepts of [FB-EHPA](#) were proposed in 1956 by *Lent*, who proposed an inflatable space suit with powered joints to assist the wearer during the flexion of suit extremities stiffened by the internal pressure [70.92]. Lately, in 1966, *Mizen* proposed, although without realizing it, the first man amplifier for civilian and military applications [70.93].

The first practical investigation was instead attempted by General Electric between 1965 and 1971, by developing the *Hardiman* [70.94] that is briefly described in the following section. Researches on [FB-EHPA](#) were resumed in 1996, when *Snyder* and *Kazerooni* proposed a novel under-actuated material handling system with 6 passive joints (2 for the legs and 4 for the arms) and 12 electrically actuated joints (6 for the legs and 6 for the arms) under force-feedback control [70.95]. System arms and legs were implemented and tested separately.

Following this renewed interest, from 2002 to 2009, three different under-actuated [FB-EHPA](#) have been developed in Japan for medium-duty applications, such as nursing care [70.83, 97], disabled or elderly assistance [70.85], and agriculture [70.100]. The best performing and most renowned system is the hybrid assistive limb (*HAL*) [70.85]. Still in Japan, in 2009, Panasonic-Activelink presented the *POWER LOADER*, a heavy-duty [FB-EHPA](#) for material handling [70.98]. In 2010, Raytheon-Sarcos unveiled the *XOS2* [70.99, 101], which is one of the most advanced and performing medium-duty hydraulically actuated [FB-EHPA](#) for military/logistics applications. One of the latest [FB-EHPA](#) is called *Body Extender (BE)* [70.102] and has been realized at the *PERCRO* Laboratory,

Scuola Superiore Sant'Anna (Italy). The [BE](#) is a full electrical machine developed for heavyweight material handling. In 2012, the French company *RB3D* has presented *HERCULE*, an electrically actuated [FB-EHPA](#) with legs similar to those of [HAL](#), but with different arm kinematics, and designed for lifting 20 kg with each arm at full horizontal extension. *HERCULE* has been developed for the French Ministry of Defense and detailed specifications are not available at present.

In this section, an overview of the basic features of some of the most relevant and advanced existing systems is provided.

Hardiman

Hardiman I is the first prototype of [FB-EHPA](#) and has been developed between 1965 and 1971 by General Electric Research (Schenectady, NY). The project aimed at developing a high-power machine for handling heavyweight materials in unstructured environments. The project was jointly supported by Engineering Psychology Programs-ONR, Naval Air Systems Command, and the Army Mobility Equipment Research and Development Center (Fort Belvoir).

The project results have been reported by *Fick* and *Makinson* in [70.94]. *Hardiman I* has a structure based on a 30-[DOF](#) kinematics including:

- 2-[DOF](#) for each end-effectors: two flexion movements of a two-phalanges finger
- 7-[DOF](#) for each arm: wrist flexion, forearm rotation, elbow, upper arm rotation, shoulder flexion, back flexion and arm abduction/adduction
- 4-[DOF](#) for each leg: hip abduction/adduction, hip flexion, knee flexion and ankle flexion
- 2-[DOF](#) for each foot: ankle inversion and ankle rotation.

The actuation system employs hydraulic actuators that require an external hydraulic circuit at 206 bar (3000 psi) with a power of 18.6 kW (25 hp). The global weight of the system is 680 kg (1500 lbs) and the exoskeleton is rated for a lift capability of 6800 N (1500 lbs). The control of the hand is completely hydromechanical (implemented with no electronic components), while the arms, legs, and feet are controlled through electrohydraulic systems. *Hardiman I* did not succeed to be tested in its full functionalities. In particular, the developers reported several problems in the implementation of the controller for the lower limbs, mainly also due to the lack of reliable electronic components and reduced computation power characterizing the technology at that time.

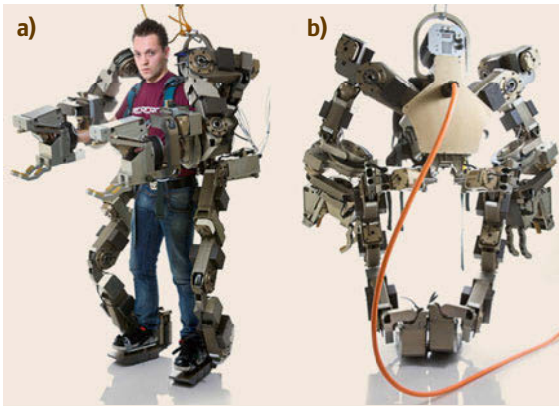


Fig.70.14a,b Picture of the Body Extender (BE): (a) system worn by a user; (b) rear view (after [70.103])

HAL: Hybrid Assistive Limb

HAL is a series of full-body exoskeleton systems, the development started in 1996 and the current version, **HAL-5**, is the first commercial version. **HAL** has been developed by *Sankai* [70.85] and his research group of the University of Tsukuba and commercialized by the company Cyberdyne, Inc. (Tsukuba, Japan) [70.103].

It is realized in two versions, the first one is for lower limbs only and the second includes the upper limbs. The exoskeleton is developed with the aim to expand, augment, and support human physical capability in the field of medical welfare, heavy work support, and entertainment. The kinematic structure features 6 passive joints (2 for the legs and 4 for the arms) and 8 electrically actuated joints (6 for the legs and 6 for the arms). **HAL** is commanded via a specially designed controller which takes into account the wearer's muscular activity through the employment of bioelectrical signals from **EMG** sensors that are disposed on wearer's skin. **HAL** weighs 23 kg in the full-body version, including batteries for an autonomy of 2 h and 40 min. Although the lifting capabilities are not specified, it is reported in [70.97] that laboratory tests have been conducted with a payload of 15 kg with each arm at full horizontal extension; however, it requires locking of the passive joints and an additional wrist support. **HAL** is currently being experimentally tested in clinics and the research group is currently working on improving the system with new control algorithms.

POWER LOADER

POWER LOADER is a full-body exoskeleton developed by Activelink Ltd, a spin-off of Panasonic Ltd, Japan. The system development was started in 2003 and the first working prototype reported in literature has been realized in 2010. **POWER LOADER** has been

developed for rescue operation in natural disaster scenarios such as big earthquakes. The mechanical design is based on an anthropomorphic design only for the arms. The legs have an anthropomorphic structure. The knee is back rotated [70.98] in order to leave more free space around the user legs. The actuation is achieved through electric motors and drivers.

PERCRO Body Extender

One of the latest full-body exoskeleton has been realized at the PERCRO Laboratory of Scuola Superiore Sant'Anna, Italy (Fig. 70.14). The developed **FB-EHPA** has been named as the body extender (**BE**) [70.104]. The **BE** comprises two identical legs with 6-DOF each, whose kinematics is isomorphic to the wearer's kinematics, and two identical arms with 5-DOF each. All 22-DOF are powered by modular highly efficient actuation units; this solution allows to reduce the power consumption, as well as to minimize the costs and efforts related to its production and maintenance. The **BE** weighs 160 kg, can provide a maximum continuous usable power of 16.5 kW, is capable of lifting 50 kg with each arm at full horizontal extension, and is designed for transporting loads up to 100 kg at a walking speed of 0.5 m/s. Potential application of this system is in earthquake disaster relief operations, where search and rescue teams need to walk across tight spaces over debris and to remove rubble in an attempt to find, release, and transport survivors. The system has been integrated and fully tested in 2010 and it is currently being improved in terms of energy efficiency and stability on uneven terrains.

Commercial Systems (Uncovered by Scientific Literature)

In the past years, two advanced commercial systems have been unveiled. The first one is **XOS II**, which is the second version of a full-body exoskeleton developed by a US company, Sarcos-Raytheon [70.99, 101, 105]. The first version of the system was completed in 2008 and the second version has been presented in 2010. The **XOS II** has been developed aiming at logistic applications in the military field. It is based on an anthropomorphic kinematics equipped with 24-DOF actuated with hydraulic systems. It weighs 95 kg and has a lifting capability of 230 N. The company is currently working on improving the energy efficiency for the realization of an autonomous (untethered) version of the system. The second device is called **HERCULES** and has been presented in 2012 by RB3D (France). It is an electric-driven system that has a lot of similarities with the **HAL-5** exoskeleton. The details of **HERCULES** have not yet been disclosed [70.106].

70.5 Control of Human–Robot Augmentation Systems

From a control point of view, the functionality of a power augmentation system should simultaneously provide (a) force amplification and (b) support to natural locomotion.

Hence, the control of exoskeleton for human power augmentation (EHPA) can be split into two major sub-systems: lower- and upper-body designs. The first sub-system cooperates with a human gait, while sustaining much of the body loads, keeping overall equilibrium and following the human motion with transparent and natural reflection forces. The second subsystem enhances human manipulation abilities through the multiplication of the arm forces during grasping operations of heavy loads.

Both components have to respect the following requisites:

1. *Stability*: The stability margin of the (linearized) control system should be large enough to cope with the environment and operator uncertainties, and to avoid uncompensated oscillations entering into resonance with the human postural control.

2. *Transparency*: The system should be highly reversible (through mechanical design or sensor augmentation) in order to allow a correct perception of the overall interaction with the environment and the proper generation of the control actions.
3. *Regular force amplification*: The gain ratio of the human force amplification should be kept as regular as possible in all interaction conditions, including a large bandwidth of interaction, different postures, and different environment interactions.
4. *Fast response*: The bandwidth and the saturation values of the position/velocity/force controllers should be as close as possible to their respective ranges used in natural motions and interaction.

70.5.1 A Historical Perspective

Yagn [70.70], first submitted a series of patents for facilitating human walking and running. At that time, the mechanism was limited to a series of springs and clutches, which altered the feet compliance during walking and used the potential energy of the springs to have a more efficient walk.

The use of active orthoses, through hydraulic servo-valves was proposed by Filippi in 1937 [70.107]. The proposed system was a knee orthosis whose motion in the sagittal plane is powered by a hydraulic piston. At that time, there was not much advancement on electric control of hydraulic systems and the joint control was supposed being regulated mechanically. A crank located on the hip moved a cam that, on its own, wound a torsional spring on the knee. The other extremity of the spring was used to regulate the piston flux.

The first documented attempt to develop a powered suit that amplifies human force was performed by Clark et al. in the early 1960s [70.39]. At that time, they proposed to design a man amplifier using hydraulic amplification. In Fig. 70.15, it is represented by the device interaction model and the basic control loop they proposed. They have limited the investigation to one single joint of movement.

In Clark et al.'s work, each joint was regulated with an independent position controller that was actuated by mechanical pistons placed closed to the human body. The control was based on an admittance scheme that translates user commands into joint velocities. This scheme had no opportunity to show the reflection of contact forces.

The design and control of whole-body active exoskeletons started in 1965 with a joint Naval Army program who supported General Electrics for the design of a whole-body EHPA (Hardiman I). The power

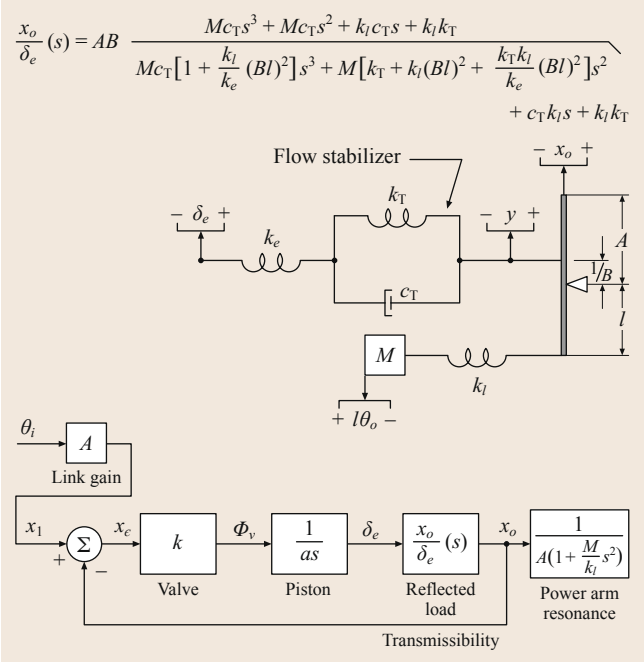


Fig. 70.15 The control of the force amplifier joint (after [70.39]). The upper scheme represents the mechanical equivalent circuit for the control of the elbow joint, and the above equation represents the associated force balance equation. The lower scheme is a block diagram that represents how the components are arranged together and how the feedback is used to control the joint actuation

augmentation target was fixed to an amplification factor (robot versus human) 25 : 1 having a nominal total force about 10 000 N.

The proposed device had 28 independent DOFs plus two grasping tools with one additional DOF each.

The control concept design of Hardiman was very ambitious. In the first attempt, the designer developed a set of mechanical servo-valves (as shown for the *master hand controller* in Fig. 70.16) placed in contact with the user's skin which responded to local pressure by deflecting the flux of hydraulic circuits [70.96].

The approach worked well only for simplified kinematics of the mechanical hand, while the dynamic interference between the serial kinematics of the arm link required the use of electrohydraulic circuits and that of a computer-developed dynamical model.

The project development stopped due to major limitations in the design and control of the lower leg. During the development, the authors only have tried unilateral electrohydraulic servos to track the motion of the user legs. The major development issue was related to the control of the leg for the body balance. The developers devised that the leg functionality changes between the stancing and the swinging phase, but the use of switches to detect the current leg phase demonstrated to be ineffective to validly cope with equilibrium and stability issues. Other issues were instead related to the power supply line (45 kW needed by the prototype) and to the kinematics differences between the master and the slave arm, which makes some motion unnatural, risky, and sometimes unstable for the driving user.

Few years later, Vukobratovic et al. [70.108] started to develop an exoskeleton to assist injured people (mostly paraplegic) to recover basic walking abilities. That work shares several features that are being imple-

mented in present power extenders. Vukobratovic et al. were able to define the following relevant features of control and stabilization loops for walking that are still valid today:

- A model reduction approach
- The method of prescribed synergies
- The use of zero moment point (ZMP) to derive the dynamic equation of motion
- The use of left–right symmetries and nominal gait cycle
- The design of a *model-based* analog motion compensator that provides to create motion synergies through a set of servomotors.

Motion synergies were computed using a nominal gait trajectory (step period = 1, step size coefficient = 1) in a reduced phase space as a reference to derive in advance the weight, the inertia, and the friction compensation torques that have to be exerted at each joint.

Figure 70.17 describes the high-level functional architecture of the controller. The adaptation for different gait conditions (from 1 to 5 s) was modulated on the precomputed trajectories through a couple of coordinated sequencers (time-base generators, TBG) that convert the absolute time into the loop phase required to determine compensation components.

The overall feedback also includes two additional feedback components, which use force sensors in the shoes to compute torque perturbation around the ZMP. These disturbances appear when the exoskeleton rotates around the leg in the stance phase or when a change of acceleration (step length/period) alters the gait from the nominal cycle.

In both cases, the author derived, through linearization of the dynamic model along the nominal cycle, a couple of static gains that map the sense forces into corrective torques that are added to the nominal hip torques.

Vukobratovic et al.'s exoskeleton worked well only for limit cycles which were close to the nominal gait trajectory it was designed for. Both Vukobratovic's exoskeleton and the experience derived from the Hardiman project showed that the control technology available at that time was premature to cope with the nonlinear, dynamic coupling effects that appears in walking and manipulation.

A renewed effort in research was performed by researchers at Berkeley University who in the middle of the 1980s promoted projects, in general called the *human extenders*, to develop arm exoskeletons that augment the arm force. Early extender projects were

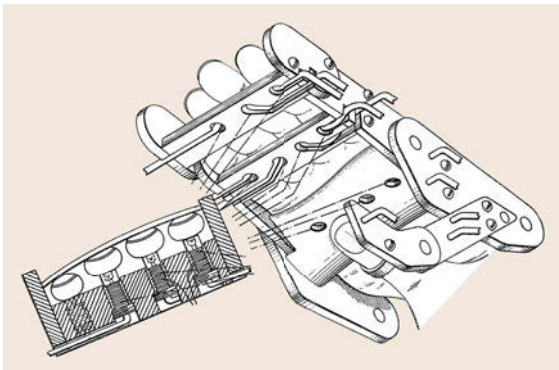


Fig. 70.16 The master hand controllers. A set of tinklers were moved according the grasping force of the user and drive the hydraulic circuit of the slave hand with a design amplification factor of 25:1 (after [70.96])

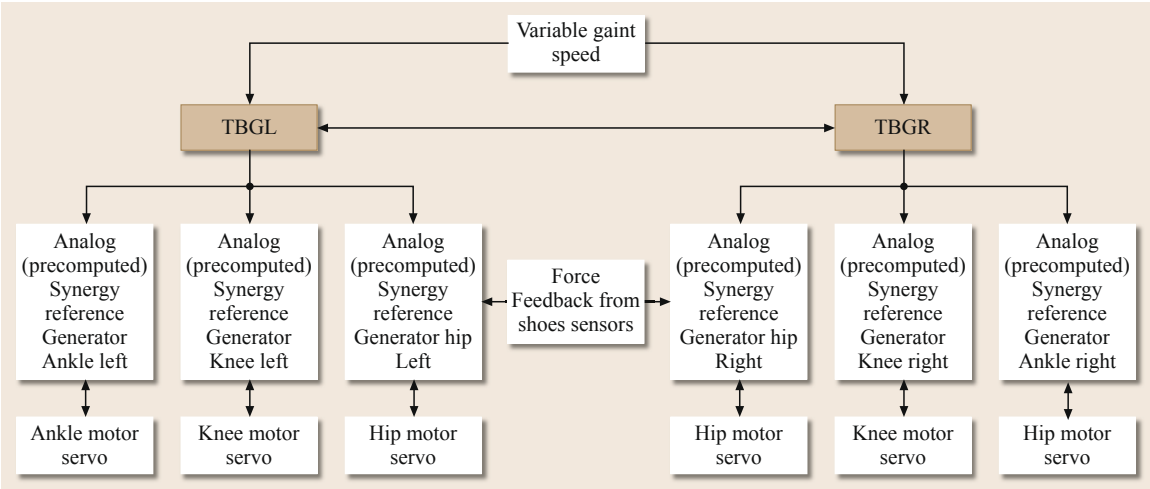


Fig. 70.17 The control structure of the 1974 Vokubratovic et al.'s exoskeletons (after [70.108]). The active device was powered with six pneumatic actuators whose references and feedback are determined through three different components: servo feedback, prescribed synergies, and force feedback for sagittal and lateral stabilization

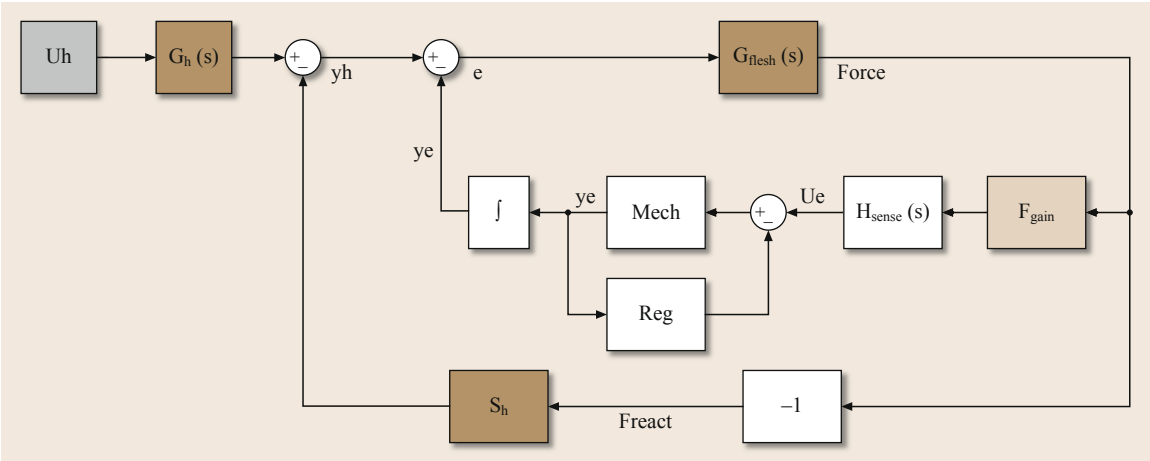


Fig. 70.18 The basic extender controller (after [70.109]). The scheme represents the extender controller as proposed by Kazerooni in 1989. The controller is based on an internal velocity controller. A given force amplifier gain F_{gain} determines the forces that are compensated dynamically with respect to the force shown to the operator

based on the combination of a robust velocity controller in feedback with a force sensor that detects user inputs.

Figure 70.18 shows the working principle of the amplification loop. With respect to previous attempts, here the use of the digital controller helped to implement more sophisticated feedback controllers that cope with the multi-input multioutput system model. The overall stability was proven through two methods: (1) a linear analysis, performed through the multi-variable Nyquist criterion on the linearized model (2) and an application of the small gain theorem that provides sufficient conditions for stability in the case

of the nonlinear model interacting with the unstructured environment. However, the stability conditions derived in [70.2] through the small gain theorem were highly restrictive and required the amplification gain to be less than 1. Subsequent author's work introduced different criteria (than fully unstructured interaction), such as typical operator and environment impedance ranges, and stability margins. Under such conditions [70.110] and using the μ -synthesis, the author demonstrated robust stability under higher force amplification gains.

An example of the amplification goal achievement with this technique and a 3 DOF arm was reported

in [70.111] as the maneuver bandwidth of 2 Hz, the vertical force amplification ratio 7 : 1, and the horizontal force amplification ratio 5 : 1.

70.5.2 Power Augmentation through Proprioceptive Sensors

This type of power augmentation systems use only sensors that are completely internal to the exoskeleton structures. These sensors have no direct contact with the human operator (e.g., motor or joint torque/position sensors).

One benefit of this approach is the reduced design complexity through the use of more conventional torque sensors and the improved stability of the reading even in the case of multiple contacts between the user and the exoskeleton structure.

As a side effect, there is no direct measurement of the force effectively felt by the user. The interaction controller decides the exoskeleton motion policy based on the estimation of the interaction force with the user.

This approach is used in the control of the Berkeley Lower Extremity Exoskeleton [70.5], and most of the intelligent assisting devices (IADs) [70.112–114].

Given the Lagrange formulation of the exoskeleton, the basic of this approach is to let the control providing a predefined percentage of the force/torque required for the motion

$$\begin{cases} \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) + \mathbf{G}_L(\mathbf{q}) = \\ \mathbf{Q} + \sum_c \mathbf{J}_c \mathbf{F}_c, \\ \mathbf{Q} = \mathbf{J}_t^T(\theta) \mathbf{F}_m, \\ \dot{\mathbf{q}} = \mathbf{J}_t(\theta) \dot{\theta}, \end{cases} \quad (70.2)$$

where $\mathbf{q}$ is the joint coordinates vector, $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{G}$, are the exoskeleton mass, Coriolis, and gravity matrices, respectively, $\mathbf{G}_L$ is the manipulated load, $\mathbf{Q}$ is the motor-torques vector reduced to the joints $\mathbf{J}_c$, $\mathbf{F}_c$ refers to the user contact forces and the respective Jacobians computed in the points of contact, and $\mathbf{J}_t$ and $\mathbf{F}_m$ represent the transmission Jacobian and the motor force/torque vector, respectively, and θ is the motor-coordinates vector.

In order to properly work, this approach also supposes to have an almost accurate model of the mechanical design ($\hat{\mathbf{M}}$, $\hat{\mathbf{C}}$, $\hat{\mathbf{G}}$, $\hat{\mathbf{J}}_c$, $\hat{\mathbf{J}}_t$) and the load to manipulate ($\hat{\mathbf{G}}_L$). In these conditions, the candidate control law is

$$\begin{aligned} \mathbf{F}_m = & (\mathbf{J}_t^T)^{-1}(\hat{\mathbf{G}}(\mathbf{q}) + (1 - \beta^{-1})\hat{\mathbf{G}}_L \\ & + (1 - \alpha^{-1})(\hat{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}} + \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}})). \end{aligned} \quad (70.3)$$

By inserting (70.4) in (70.2), we have

$$\begin{cases} \alpha^{-1}(\hat{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}} + \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}) + \beta^{-1}\mathbf{G}_L(\mathbf{q}) \\ = \sum_c \mathbf{J}_c \mathbf{F}_c + \varepsilon(\mathbf{q}) \\ \varepsilon(\mathbf{q}) = (\mathbf{M}(\mathbf{q}) - \hat{\mathbf{M}}(\mathbf{q}))\ddot{\mathbf{q}} + (\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) \\ - \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}}))\dot{\mathbf{q}} + (\mathbf{G}(\mathbf{q}) - \hat{\mathbf{G}}(\mathbf{q})) \\ + (\mathbf{G}_L(\mathbf{q}) - \hat{\mathbf{G}}_L(\mathbf{q})), \end{cases} \quad (70.4)$$

where the model error is expected to converge toward zero.

Equation (70.4) shows how the contact forces perceived by the user can be reduced by a static (β) and/or a dynamic (α) amplification factor. As a matter of fact, if the simplification operates correctly ($\varepsilon \rightarrow 0$), the pilot will only feel on his own body a percentage of the carried load (β^{-1}) plus a percentage of the exoskeleton dynamic (α^{-1}).

In the case of a walking exoskeleton, the above control model is switched according to the stancing foot, or in the case of double stancing (the weight is distributed on both feet), a simplified zero-moment-point (ZMP) rule is applied [70.115]

$$\begin{cases} m_{\text{TR}}x_{\text{TR}} = m_{\text{TL}}x_{\text{TL}}, \\ m_{\text{TR}} + m_{\text{TL}} = m_L, \\ \frac{x_{\text{TR}} + x_{\text{TL}}}{2} = x_g, \end{cases} \quad (70.5)$$

where x_{TR} and x_{TL} are the stancing position of the right and left feet, respectively, x_g is the projection of the center of mass on the walking plane, m_L is the overall load mass, and m_{TR} and m_{TL} are the mass components to be distributed on the right and left control models, respectively.

Equation (70.5) is used as a means to separate the closed-loop kinematics into two (quasi) symmetrical equations, similar to (70.2), that only refer to the left- and right-leg dynamics. The load is consequently distributed among the two legs, thus generating two *decoupled* control models, one for each leg.

Discussion 70.1

Experiments on such a kind of controller were performed at UC Berkeley. In [70.75], the system proved to be efficient to compensate completely the weight ($\beta^{-1} = 0$) with a good dynamic scale power amplification factor ($\alpha = 10$), and that the resulting system is usable for walking at an average speed of 1.3 m/s with a transported payload of 70 kg (including the exoskeleton weight).

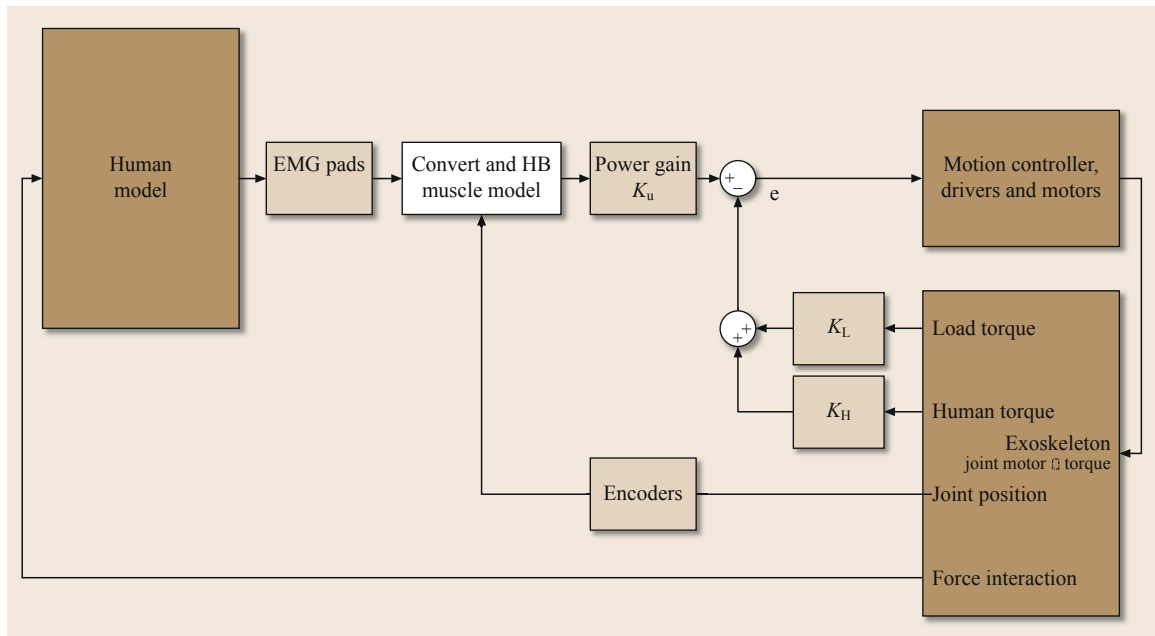


Fig. 70.19 The basic EMG controller (after [70.116]). The myo-electric signals were processed to derive a control signal through a sequence of (1) high-pass filter; (2) signal rectification (absolute value); (3) low-pass filtering; (4) normalization versus a nominal setup isometric contraction. The sign of the contraction is detected as a combination of pure agonistic–antagonistic contractions

The proposed design, however, suffers from a number of drawbacks that limit this control architecture being used in a more flexible interaction environment:

- The measurement of interaction torques made at the joint level makes it indistinguishable, whose interaction caused the reading, be it a voluntary movement provided by the user or an involuntary interaction provided by the environment. In both cases, the control amplifies these effects regardless of the fact that the original stimuli were provided by the user.
- The sensor and the mechanical model assumed in the discussed work only deal with a rigid mechanical design model whose structures risk to be cumbersome and dangerous when the load to be carried/manipulated is high. Flexible designs may manipulate higher loads at the cost of more complex control design [70.38].
- The robustness of the control is demanded to the accuracy of the model and the design of the compensation gains. When no gain is programmed ($\alpha = \beta = 1$), the feedback is zeroed and the user perceives all the passive effects of the dynamics. Increasing these gains lowers the stability margin in a way that is dependent on the quality of the model approximation.

70.5.3 EMG Force Control and Power Augmentation

Notwithstanding the fact that EMG-based arms were already developed in the early 1980s, power-augmented systems based on EMG signals only appeared at the beginning of the 2000s. In 2001, *Rosen et al.* [70.116] proposed a powered exoskeleton system based on the myosignal analysis (as shown in Fig 70.19).

In order to associate a map between the myo-electric signals and the amount of exerted force, Rosen first detected the level of activation, then he applied a basic muscle contraction/elongation model as described by *Hill* [70.117] during his investigation on tetanic contraction and by *Winter* [70.60] for antagonistic muscle analysis. According to Hill's model, the force correlates the combined effects of muscle activation, muscle elongation, and muscle speed to a well-known state equation

$$F = \frac{aF_0(v_0 + v)}{(vF_0 + av_0)}, \quad (70.6)$$

where F is the force exerted by the muscle, v is contraction velocity of the muscle, F_0 is the maximum isometric force generated by the muscle, v_0 is the muscle maximum velocity, and a is the coefficient of shortening heat.

Such a model has been applied to all involved muscles $M_f = M_f(U_{\text{emg}}, \theta_m, \dot{\theta}_m)$, to determine the moment M_f induced on the elbow joint angle θ_m , by the muscle fibers f . In addition to the muscle bio-signal, the control closed loop used two more data from sensors: (1) a measurement of the external load and (2) the overall momentum applied by the operator on the exoskeleton.

The underlying basic idea is that the muscle signal operates as an external loop that provides a reference for an internal moment controller. The three gains in the controller K_L , K_H , K_u define, respectively, the internal loop force gain K_H versus K_L , and the overall EMG signal tracking bandwidth.

In a similar effort to the Rosen elbow extender, Kawai et al. [70.118] proposed a 1-DOF-actuated wearable device that lowers the internal backbone strain during pick-up tasks in order to prevent from lumbago. The device senses the average back angle (measured through a potentiometer) and the EMG strain on the thigh muscles. The motor control for the device is determined through a state machine based on a typical load pick-up and release procedure. The threshold values for switching between phases were determined through a test with a nominal load.

In [70.119] and [70.82], the EMG data are employed to control the HAL-3, walking assistant, and exoskeleton. The control algorithm is a combination of a finite-state machine with a torque control. Two force sensors placed in soles of the shoes serve to determine the floor-reaction forces and to switch among phases. Each phase is then used to determine in which mode the user knee is moving (active, passive or free). The joint motors are consequently controlled using Table 70.1

In different phases of motion, the joint control adopts a computed torque approach plus two components proportional to the myo-signals of flexion and extension

$$\begin{aligned} \tau_{\text{joints}} = & K_{\text{fl}} \text{EMG}_{\text{fl}} - K_{\text{ex}} \text{EMG}_{\text{ex}} \\ & + (I - M) \ddot{\theta} + (D - B) \dot{\theta} \\ & + C(\theta, \dot{\theta}) + K(\theta_0 - \theta), \end{aligned} \quad (70.7)$$

Table 70.1 The HAL dual-phase model. The phase 1 relates to the swinging leg and phase 2 relates to the stancing leg. In each phase, the table indicates the type of control to be implemented on the relative exoskeleton joint

Joint	Phase 1		Phase 2	
	Direction	Mode	Direction	Mode
Hip	Flexion	Active	Extension	Active
	Flexion		Flexion	
Knee	↓	Free	↓	Passive
	Extension		Extension	

where I and D are the inertia and viscous coefficients, respectively, as estimated through a recursive least squares auto regressive estimator (ARX) identification, C includes all Coriolis and gravity effects, M , B and K represent the target inertia, impedance to show to the operator. The term $\tau = K_{\text{fl}} \text{EMG}_{\text{fl}} - K_{\text{ex}} \text{EMG}_{\text{ex}}$ represents the estimated muscle torque whose conversion factors were determined through experimental tests.

The measure assistance level is close to 60% during flexion activities and to 85% during extension. In its most recent version, the HAL-5 adds contributes from accelerometers and gyroscope mounted on the backpack for better posture estimation [70.120]. HAL-5 extends the principle of operation of the lower body control to the user arm, by allowing the user to hold and carry an additional weight of 40 kg. HAL-5 extends the control with a greater number of phases (swing, landing, and support) and provides different control gains to optimize each phase [70.121].

The above EMG controllers only work fine when the developers are able to find two antagonistic muscles whose flexions and extensions can be directly related to the overall force exerted on a user joint (e.g., the biceps and triceps for the elbow joint). If this is not the case, Kiguchi et al. showed out how fuzzy controllers may estimate joint torques from several torques. In [70.122], they showed how to decode shoulder torques by combining the EMG signals recorded from eight different muscle sources. Such a fuzzy network has been coupled in the control of a 3-DOF mobile exoskeleton [70.123] to assist motion in highly impaired people.

70.5.4 Power Augmentation through Exteroceptive Sensors

High-force power augmentation systems require a different approach with respect to the proprioceptive and the EMG sensing approaches. In such devices, the flexibility of the structure and the high torques required at joints prevent the use of indirect measures of the force/torque exchanged between the device and the user. Moreover, the Hardiman approach, which integrated a master exoskeleton and an outfitting slave exoskeleton as a unique teleoperation system proved not to be functional [70.94].

Two systems have proved so far to reach this target in an operational and fully functional scenario: the Sarcos/Raytheon XOS Exoskeleton for the arms and legs [70.105] and the BE developed by PERCRO at Scuola Superiore Sant’Anna. Both of them are based on a similar working principle: the user body is directly attached to the exoskeleton in a predefined numbers of points, e.g. the two feet, the hands’ handles, and a shoulder harness for the BE; and additional interac-

tion at the pelvis for the XOS. The interaction forces exchanged between the exoskeleton and the user are measured at these points and used to simultaneously control equilibrium, force amplification, and motion control.

On the other side, the two systems differ for a number of technical details: the XOS design is light, adherent to the user body and based on rotary-hydraulic actuators, the BE instead mimics the weight distribution of the human body, the exoskeleton does not touch the user body except for the predefined contact points and can automatically adapt to different human percentiles, and finally, all the actuation structure is based on a unique high-torque electrical motorization.

Very few data are documented about the operation of the XOS system and much of the information available is contained within its related patents, instead the kinematics and the control of the BE are described in several documents [70.104, 124].

70.5.5 Control Schemes

The BE control is organized as a decentralized control, where each joint is supervised by a separate electronics. Figure 70.20 shows the PERECRO-BE device. All the electronics are organized in four clusters which respectively map to the single human limbs. The interconnection between joint controllers is achieved through four separate EtherCAT-buses.

All connections converge into a central electronics placed in the trunk backpack, which manages high-level control of walking, stability, and manipulation.

A unique type of motorization as well as a unique type of low-level controller is implemented in each joint. Figure 70.21 highlights the interaction between the internal control loops and the higher control level. The internal controllers operate at a very high rate (2.5 kHz) and provide to estimate the joint velocities. At limb extremities, these controllers also acquire the information recorded by the embedded force sensors. The modularity of the architecture and the structure of the information do allow a high scalability of the system and a regular scheduling of the local and higher controllers.

The two components highlighted in Fig. 70.21 as *force control* and *feed forward control* are managed at the central level at 1 kHz basic control rate. The first generates, using the sensor force information, a velocity command that is forwarded to each limb cluster, whereas the second combines force information with posture and velocity information to define feedforward commands that can be directly added to compensate weight, loads or other gravity/inertial effects on the exoskeleton joints.

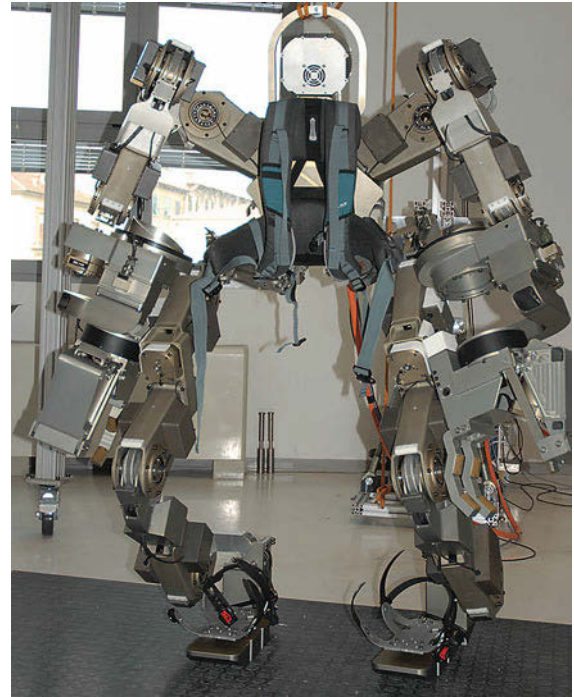


Fig. 70.20 The PERECRO-Body Extender has been already defined (BE). The BE is a whole-body exoskeleton structure designed to lift and manipulate 50 kg load per arm in the worst case conditions. The device has five attachment points with the user body: the two boots, two handles embedded in the grippers and the trunk corset. In addition to the internal sensors (position, force, and gyroscopes), force sensors embedded in the attachment connection help to determine the proper motion commands

Given its flexible structure, the central controller can operate on the joint controllers in different operational modalities; among these are: admittance controller, impedance controller, and feedback linearization controller.

Admittance Controller

Different control strategies have been implemented to move both the upper arm and the lower body part of the exoskeleton. Four basic schemes of admittance controller are implemented to manage the exoskeleton during walking and manipulation activities:

- Arm admittance
- Swinging leg
- Stancing leg
- Double stancing leg.

The basic scheme is the arm-admittance controller. In this approach, the local force sensed at the inter-

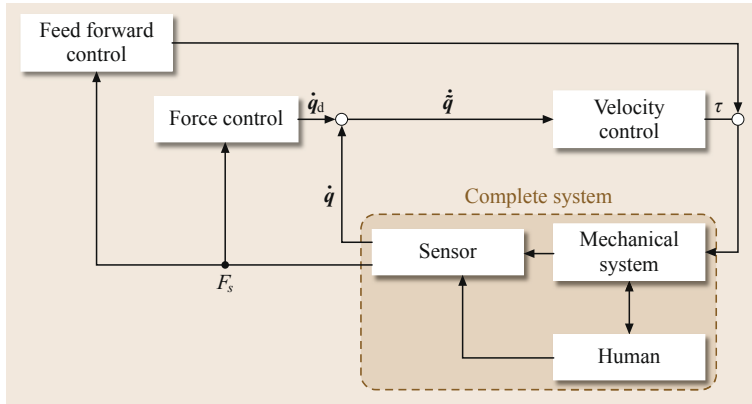


Fig. 70.21 The basic BE control structure. The internal velocity controllers are placed in the exoskeleton joints and locally perform a velocity servo loop (proportional derivative) which is enhanced by a direct feedforward torque. Both the inner-loop gain parameters and the external feedforward torque can be commanded from the higher level central control unit. This structure is repeated identically for all the exoskeleton joints

face is projected to the trunk reference system through the appropriate coordinate transformation. Its value is amplified through a gain factor and smoothed through a first-order low-pass filter that remove noisy effects. This reference signal is then back-propagated to the joint by using the inverse of the limb Jacobian.

$$\dot{q}_{Ld} = \mathbf{J}_L^+ \frac{p_f \mathbf{K}_{LV}}{s + p_f} \mathbf{R}_h^{\text{Tr}} \mathbf{F}^h, \quad (70.8)$$

where $\mathbf{F}^h$ is the handle force/torque vector as read by the sensor, $\mathbf{R}_h^{\text{Tr}}$ is the rotation matrix that maps to the appropriate trunk reference system, $\mathbf{K}_{LV}$ is a force/velocity gain, p_f is the smoothing frequency, and $\mathbf{J}_L$ is the appropriate limb Jacobian that describes the motion of the limb with respect to the trunk.

In addition to the above velocity commands, the control system also computes in real time the gravitational effects produced by the exoskeleton joints and provide to compensate them through the feedforward input (τ_{ff}) of the joint velocity controllers.

$$\tau_{\text{ff}} = \tilde{\mathbf{G}}(\mathbf{q}) \mathbf{R}_w^{\text{Tr}} \begin{bmatrix} 0 \\ 0 \\ 9.81 \end{bmatrix}, \quad (70.9)$$

where $\tilde{\mathbf{G}}$ is the gravity contribution matrix ($\text{DOF} \times 3$) that maps forces generated by the gravity to joints, $\mathbf{R}_w^{\text{Tr}}$ is the rotation matrix that describes the arm orientation with respect to a world frame having the gravity vector aligned with the z -axis.

The motion behavior generated to the programmed feedback policy can be examined through a two-step analysis. The internal position controller can be made asymptotically stable through standard robust control techniques. While the external admittance loop, which involves the human operator, exploits an intrinsically passive behavior, through the display of a pure viscous

force to the operator. Hence, until the outer loop bandwidth is sufficiently smaller than the internal velocity servo, the two loops do not interfere [70.125].

The arm-admittance (70.8) scheme, also applies to floating legs which swing during walking. In such a case, the controller uses the forces measured by the booths which have been biased using offset values that ensure a stable contact among the user's foot and the exoskeleton booth.

During the stancing phase, the information provided by the force sensors in the booth is useless. Hence the force sensor between the corset and the trunk backpack (backpack force) is used as a trajectory generator for the leg motion. The reference trajectories are generated with a unique, dual step, procedure which do not change being the exoskeleton stancing on one or two legs.

In the first step, the *backpack force* has been determined. This force is filtered and amplified in the same way as for the handle admittance control. This operation generates a velocity vector ($\mathbf{v}_b, \boldsymbol{\omega}_b$) that applies to the backpack. In the second step, the central controller maps the same velocity vector to leg motion using a velocity map relationship that uses the direct kinematic between the trunk and the booths' soles. The kinematic vector, $\mathbf{r}_1(\mathbf{q})$, that describes the booth position with respect to the *backpack force* sensor is

$$\begin{cases} \mathbf{v}_f = \mathbf{v}_b + \boldsymbol{\omega}_b \wedge \mathbf{r}_1(\mathbf{q}), \\ \boldsymbol{\omega}_f = \boldsymbol{\omega}_b. \end{cases} \quad (70.10)$$

The approach maps the force felt by the corset backpack to the proper leg motion regardless the knowledge of the ZMP position.

Feedback Linearization Controller

The major limitation of the admittance control is the lack of transparency. The user who wears the power augmentation exoskeleton only feels forces that are proportional to his speed, and the feedforward component

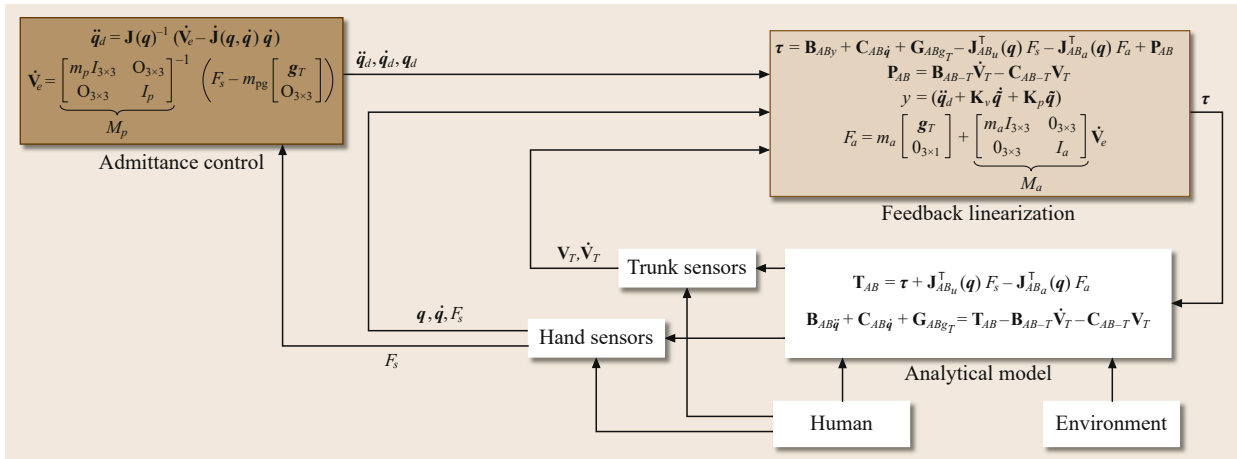


Fig. 70.22 The second-order admittance controller with feedback linearization. In this control scheme, the control input provided by the pilot generates a reference acceleration information for the limb. The feedback linearization provides to compensate the inertial/centrifugal/gravity effects of the exoskeleton and to map user input in proper acceleration information at the contact point. Moreover, the appropriate force amplification factor programmed at the sensor provide to establish an equilibrium among the environment interaction and the user commands

is only used to enlarge the control bandwidth and reduce the nonlinearity due to different postures.

However when the user touches any object, none of the contact force interferes with the exoskeleton motion creating in such a way an infinite force gain. While from the one side this is highly beneficial for joint stability, as a result it compromises the ability of the user to operate fine, scale force manipulation, tasks.

In order to recover this functionality, the BE implements on the same internal control structure two alternative control policies:

- A second-order admittance controller
- An admittance adaptive controller.

The second-order admittance controller collects user inputs to determine torque commands to the low-level joint controllers. This type of controller has been tested only on the upper body of the exoskeleton for the two relevant issues:

- The arms require greater manipulation capabilities and a better transparency
- The limited transparency of the leg motion reduces the interference between arm dynamics and trunk motion thus improving the overall stability.

The principle of operation for power augmentation is as follows (the related numerical equations have been reported in Fig. 70.22):

First, a force input is collected at each user handle. We suppose this force as being driven the interaction of

a virtual mass with the given inertia properties (m_p, I_p) and a separate weight property (m_{pg}).

Hence the resulting handle (end-effector) velocity (V_e) will be determined as a direct integration of the user force as applied on this virtual mass, and the joint velocities as direct differentiation of the motion Jacobian (box admittance control 70.22).

The feedback linearization control here comprehends four components:

- The $B_{AB} \ddot{q} + C_{AB} \dot{q} + G_{AB} g_T$ component, which takes into account the tracking error y , and the rotated gravity vector g_T
- The effective user force F_s , considered as being equal to the sensor read, and already applied on the exoskeleton structure
- The weight and inertial effects produced on the exoskeleton by the carried load (m_a, I_a) moved at the prescribed velocity (V_e)
- And the additional inertial and Coriolis effects provided by the moving trunk (P_{AB}).

As for the first-order admittance controller, the stability of the rigid model here can be ensured through the analysis of the linearized model. Combining the required equations, it can be derived that the robustness of the system is only affected by the amount of the inertia in the virtual mass properties (m_p, I_p). This property is unrelated from the power augmentation factor (m_a/m_p).

This is the reason why it is wise to decouple among the virtual mass (m_p, I_p) and the weight used for gravity

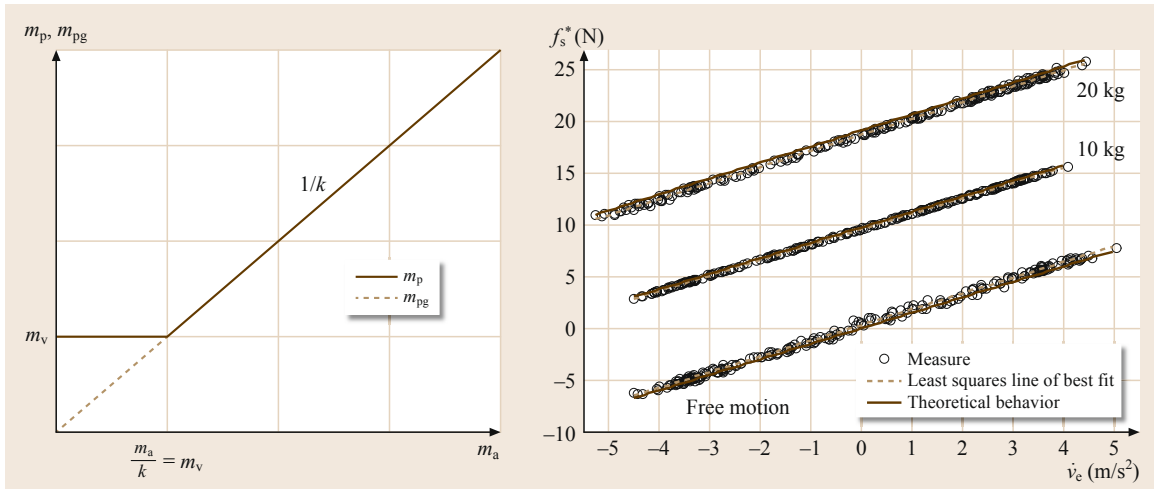


Fig. 70.23 Power augmentation profile. The power augmentation coefficient (k) is defined as the ratio of the carried load versus the perceived load. In the BE approach this ratio is represented as a piecewise linear approximation (left drawing). The quality of the control, tested on 1-DOF of the BE, has integrated with the adaptive policy and is shown on the right

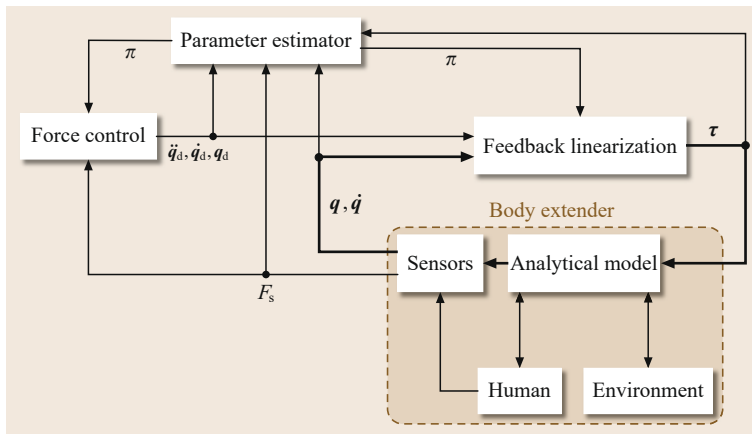


Fig. 70.24 The admittance adaptive controller with feedback linearization. A standard parameter estimator procedure has been applied to the robot structure in order to achieve online identification of the carried load. To simplify the computation and improve accuracy of estimation, the procedure assumes that the grasped object has regular mass properties and can be described with only two parameters as shown in Fig. 70.22

compensation (m_{pg}). The last not affecting the overall control stability.

Finally, the power augmentation factor has been defined as a piecewise linear approximation of the m_a versus m_p ratio which saturates for lower values of m_p in order to preserve overall stability (Fig. 70.23 left).

In order to work appropriately, the second-order admittance model requires an approximate estimation of the carried load (Fig. 70.23 right). It is supposed that this information to be subjected to the following conditions: the grasp is stable during manipulation, and the load does not change frequently.

Under these conditions, it is possible to use the motor currents as torque sensors that estimate the carried load. The principle of operation is reported in Fig. 70.24. Under the hypothesis that the load is stable and not frequently changing, the estimator can operate in lower frequencies.

Several tests to check the quality of estimation and the real-time adaptation to load change have been performed. In Fig. 70.24, the specific case of three different loads are reported. Attached to the video material of the present chapter the mass load/unload operation have been shown.

70.6 Conclusions and Further Developments

The presented review outlines some historical and state-of-the-art developments of wearable robotic systems for human–robot augmentation. Although EHPA systems are receiving an almost increasing interest from the robotics community, both from the research and from the commercial point of view, at present, the robotics technologies associated to their development are mainly derived from existing and well-established components. The lack of appropriate robotics components purposely developed for utilization on a *wearable* robotic system is mainly due, as testified by the existing research prototypes and commercial products, to a design approach that reflects the same methodologies pursued since the beginning for the design of industrial robots.

The design of a robotics system that must be worn by the human operator during a continuous operation also in unstructured environments should necessarily hamper design criteria, such as safety, fatigue, transparency, etc., that are only sometimes minimally considered for industrial robots.

From the above analysis of different typologies of EHPA systems, it comes out that the availability of adequate actuation components is fundamental to fulfill the basic functional requirements in terms of total weight, dynamics behavior, and control aspects. However, what is needed for the future research in this extraordinary

interesting and challenging field of research in robotics deals primarily with a new radical design philosophy centered on biomechanical aspects of humans behavior. In particular, a novel methodology considering as primary criteria the issue of energy consumption, not only for the wearable robotic system itself but also in terms of the complex resulting system human operator–wearable robot seems a fundamental prerequisite for future developments.

As indicated in the previous sections, so far true advantages of exploiting an EHPA system in different real-application scenarios are still to be demonstrated. In fact, so far, research developments have been primarily devoted to the physical design and realization of wearable robots, without addressing the successive phase of validation and performance assessment in a true real environment. This aspect should enter as a prominent component for future developments of the research on EHPA.

The field of wearable robots is rapidly expanding and the associated challenges in terms of design methodologies and ad-hoc robotics technologies just began to be understood in their full meaning. The motivations for future developments in this field should always firmly maintain human operator’s needs as the central focus of the research.

Video-References

-  VIDEO 146
- Arm light exoskeleton (ALEx)
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/146>
-  VIDEO 148
- Arm-Exos
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/148>
-  VIDEO 149
- Body extender transversal joint
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/149>
-  VIDEO 150
- Hand-exoskeletons
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/150>
-  VIDEO 151
- Collaborative control of the Body Extender
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/151>
-  VIDEO 152
- Body Extender – A fully powered whole-body exoskeleton
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/152>
-  VIDEO 180
- L-Exos for upper-limb motor rehabilitation
available from <http://handbookofrobotics.org/view-chapter/70/videodetails/180>

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Multimedia Contents



71. Cognitive Human–Robot Interaction

Bilge Mutlu, Nicholas Roy, Selma Šabanović

A key research challenge in robotics is to design robotic systems with the cognitive capabilities necessary to support human–robot interaction. These systems will need to have appropriate representations of the world; the task at hand; the capabilities, expectations, and actions of their human counterparts; and how their own actions might affect the world, their task, and their human partners. *Cognitive human–robot interaction* is a research area that considers human(s), robot(s), and their joint actions as a cognitive system and seeks to create models, algorithms, and design guidelines to enable the design of such systems. Core research activities in this area include the development of representations and actions that allow robots to participate in joint activities with people; a deeper understanding of human expectations and cognitive responses to robot actions; and, models of joint activity for human–robot interaction. This chapter surveys these research activities by drawing on research questions and advances from a wide range of fields including

71.1	Human Models of Interaction	1908
71.1.1	Mental Models of Robots	1908
71.1.2	Social Cognition	1911
71.2	Robot Models of Interaction	1914
71.2.1	Developmental Models	1915
71.2.2	Robot Spatial Cognition	1915
71.2.3	Symbol Grounding	1915
71.3	Models of Human–Robot Interaction	1916
71.3.1	Dialog–Based Models	1916
71.3.2	Simulation–Theoretic Models	1921
71.3.3	Intention– and Activity–Based Models	1922
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computer science, cognitive science, linguistics, and robotics.

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When people interact with each other, they draw on mental models of themselves, of their interaction partners, of the immediate context of the interaction, and of their broader physical, social, and cultural context. These models help them predict the actions of their interaction partners and make decisions about their own actions. To effectively interact with people, robots need similar models that help them determine their own actions and predict the actions of their users. *Cognitive human–robot interaction* (**HRI**) is a research area that seeks to improve interactions between robots and their users by developing cognitive models for

robots and understanding human mental models of robots. A central tenet of cognitive **HRI** is that humans, robots, and the context of their interaction form a complex cognitive system situated in the real world. A key research activity in the field involves the development of frameworks to represent this system [71.1–3]. This activity is informed primarily by research in cognitive science that develops frameworks to represent human cognitive systems. These frameworks include physical symbol systems [71.4], situated actions [71.5,6], and those that combine symbolic and situated perspectives,

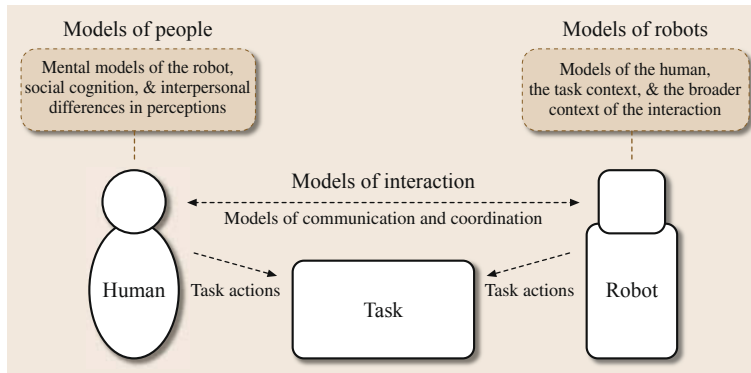


Fig. 71.1 A visual summary of the research activities in cognitive HRI

such as activity theory [71.7] and distributed cognition [71.8]. While the discussion on what framework best represents HRI as a cognitive system is ongoing, research in cognitive HRI involves the development of both symbolic and situated representations. More specifically, research activities in this area include (also illustrated in Fig. 71.1):

1. *Human models of interaction:* Building an understanding of people's mental models of robots, how people perceive robots and interpret their actions and behaviors, and how these perceptions and interpretations change across contexts and user groups.
2. *Robot models of interaction:* The development of models that enable robots to map aspects of the interaction into the physical world and develop cognitive capabilities through interaction with the social and physical environment.
3. *Models of HRI:* Creating models and mechanisms that guide human–robot communication and collaboration, action planning, and model learning.

This chapter surveys existing efforts in these research areas, drawing on research questions and advances from a wide range of fields including robotics, cognitive science, and linguistics.

71.1 Human Models of Interaction

Robots are expected to increasingly enter everyday environments – outside of factories and laboratories – including homes [71.9, 10], offices [71.11], and classrooms [71.12, 13]. In these contexts, robots will need to coexist and collaborate with a wide variety of users, such as children and the elderly, many of whom will not be technically trained. Accordingly, there is a growing research emphasis in cognitive HRI on identifying the mental models people use to make sense of emerging robotic technologies and investigating people's reactions to the appearance and behaviors of robots. This research aims not only to improve the ease of use of robots by designing them to fit human mental models, but also to gain new insights about human cognition and behavior. With the latter goal in mind, researchers also use robots to embody specific theories of human cognition that are then evaluated through HRI studies.

71.1.1 Mental Models of Robots

Research in human–computer interaction has shown that people's attitudes and behaviors toward digital technologies often follow the social rules established in

human–human interaction [71.14]. It is reasonable to expect that people will similarly interpret the interactive behaviors of robots in social ways. Cognitive HRI researchers continue to investigate the extent to and conditions in which this maxim applies to HRI as they use their understanding of human social cognition to develop robotic platforms adapted to users' expectations and behaviors. In the process of evaluating such robotic platforms, researchers explore people's mental models of robots and identify areas in which users' expectations and understandings of robots may not be born out by the robot's appearance or behavior in ways detrimental to the HRI experience. Knowing which mental models people are using to interpret robot behavior not only helps roboticists to understand HRI more deeply, but also helps them in designing appropriate behaviors for the robot.

Models Ascribed to Robots

Extensive research by Turkle et al. [71.15, 16] examines how people, including children and older adults, make sense of their novel interactions with social robots such as Kismet, Cog, PARO, Furby, and My Real Baby.

These studies show that people apply a variety of mental models relating to animacy, sociality, affect, and consciousness to explain their experiences and emerging relationships with robots. Some research participants approached robots in a scientific-exploratory mode, interpreting a robot's actions in an emotionally detached and mechanistic manner. Others took a relational-animistic approach, investing in the interactions emotionally and treating robots as if they were living beings, such as babies or pets. The ways in which participants described the robots verbally did not always fit with the way in which they interacted with them – a person who says the robot is *only a mechanical thing* may still act toward the robot in a nurturing manner, such as soothing a crying My Real Baby [71.16, p.118]. This corresponds to previous findings in human–computer interaction (HCI) which suggest that people *mindlessly* apply social characteristics to computers [71.17]. Field studies with the seal-like robot PARO have shown that robots can also act as *evocative objects* that spark reflections on previous relationships and events (e.g., with a grandchild, spouse, or pet), which users then use to make sense of their interactions with the robots [71.18, 19].

In addition to identifying the mental models people use to interpret their experiences with robots, researchers study the effects from deliberately incorporating specific social schemas into robot design. *Anthropomorphism*, or the attribution of human characteristics to nonhuman (e.g., animal or artifact) behavior, is an interpretive schema that has been of particular interest to HRI researchers. Some scholars, such as Nass and Moon [71.17], critique anthropomorphic explanations as false and misleading. Others, including Duffy [71.20] and Kiesler et al. [71.21], suggest that the deliberate use of anthropomorphism can benefit social robot design by taking advantage of people's propensity to interpret events and other agents socially to make robot behaviors more understandable to users. This interpretation raises the question of which characteristics of the robot or the interaction are instrumental in inciting people to anthropomorphize robots and has inspired researchers to study a variety of socio-cultural cues, behaviors, and task contexts. Kiesler et al. [71.21] showed that people anthropomorphize a physically embodied robot more readily than an on-screen agent, and people behave in a more engaged and socially appropriate manner while interacting with the co-present robot. People also anthropomorphize robots they interact with directly more than they do with robots in general, and with robots that follow social conventions (e.g., polite robots) more than those that do not [71.22]. The personal characteristics, such as personality, of the human interaction partner can also affect their mental models of robots. For example, users with low emotional stability and extraversion

scores were found to prefer mechanical-looking robots to human-like ones [71.23].

As might be expected, a robot's human-like appearance can have a positive effect on people's propensity to anthropomorphize [71.25]. Obversely, too high a level of human-likeness may place the robot in the *uncanny valley* [71.26]. The *uncanny valley* refers to a dip in the hypothetical nonlinear graph describing the relationship between a robot's human-likeness and a human's emotional response to it, suggesting that a robot with a very high degree of human-likeness coupled with some remaining nonhuman qualities will make users uncomfortable. This hypothesized effect essentially describes what happens when a person's mental model of the robot as human is not born out by its interactive capabilities. Various cognitive aspects of this hypothesis have been studied, suggesting that the construct is multidimensional [71.27, 28] rather than two-dimensional (2-D), as depicted by Mori [71.26]. Furthermore, research suggests that the mismatch between different dimensions, rather than any quality alone, can cause a dissonance that leads to people's discomfort with robots. MacDorman et al. [71.24] show that incongruencies between a robot's appearance and movement can diminish anthropomorphic attributions (Fig. 71.2). A similar result was found by Saygin et al. [71.29], who used functional magnetic resonance imaging (fMRI) to show that the human action perception system made distinctive responses to the mismatch between the level of human-likeness of a robot's appearance and motion but not to appearance or motion alone. Mismatches in the human- or robot-like qualities of an on-screen robot's voice and appearance were also shown to heighten people's sense of the character's eeriness – people found

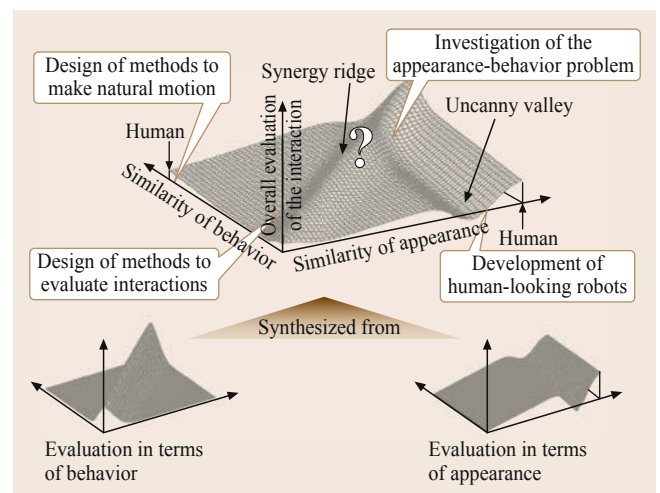


Fig. 71.2 An extended notion of the uncanny valley which includes appearance and behavior as significant variables (after [71.24])

both a robot with a human voice and a human with a robot voice to be creepy [71.30].

Mental Models in Robot Design

Researchers may deliberately include specific anthropomorphic schemas to promote user behaviors that aid robots in performing their tasks. One common example is the use of the *baby schema* – a soft round appearance, large eyes, and proto-verbal utterances – in Kismet [71.31] (Fig. 71.4), Muu [71.32] (Fig. 71.3), and Infanoid [71.33] to encourage people to anthropomorphize robots. This schema is also useful in that it can incite people to behave in a nurturing manner toward robots in the interest of scaffolding the robots' learning in a way similar to infant–parent interactions. A robot's *perceived* gender can also have an effect on people's mental models of the robot's knowledge of certain topics; for example, in one study a female robot was expected to be more knowledgeable about dating than a male robot [71.34]. While certain mental models become operational as soon as a person starts interacting with a robot (e.g., gender, age, human-likeness), people can adapt their mental models of a robot's capabilities when given additional information about the robot's personal characteristics, such as the robot's country of origin or the language it speaks [71.35]. Goetz et al. [71.36] showed that matching a robot's *personality* to the task it is supposed to perform can have a significant effect on its efficacy: people were more responsive to a robot that had a serious, rather than an entertaining, demeanor when its job was to motivate them to exercise. Also focusing on *task models* in HRI, Lee et al. [71.37] showed how people use their existing utilitarian and relational models of service to set expectations for their interactions with a service robot. These models also affected the preferred ways in which the robot should make up for any mistakes it makes in service – people with a utilitarian mental model of service preferred to receive compensation, while those with a relational model responded well to an apology.

As interactive robots are developed and used all over the world, researchers have also started exploring how *cultural models* [71.38] affect people's perceptions of and interactions with robots. Social and behavioral norms are culturally variable, so we can expect users' understanding and adoption of socially interactive robots to differ accordingly. Cross-cultural research in HRI largely supports this expectation. Evers et al. [71.39] showed that users from China and the US respond differently to robots. Further research by Wang et al. [71.40] suggests that specific cultural models regarding communication norms, particularly explicit and implicit modes of communicating information and intent to interaction partners, affect people's

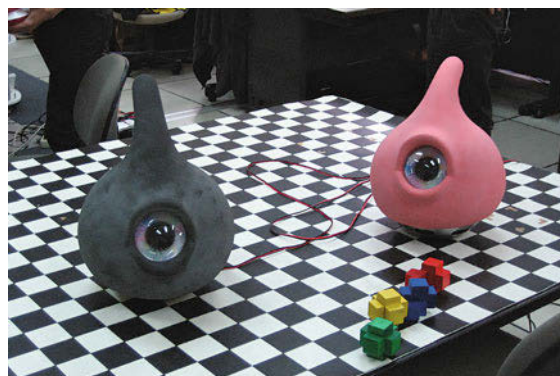


Fig. 71.3 Muu's big eyes and soft round body are designed according to the *baby schema*. Using two robots that can interact with each other instead of one suggests a relational understanding of agency (courtesy of Šabanović)

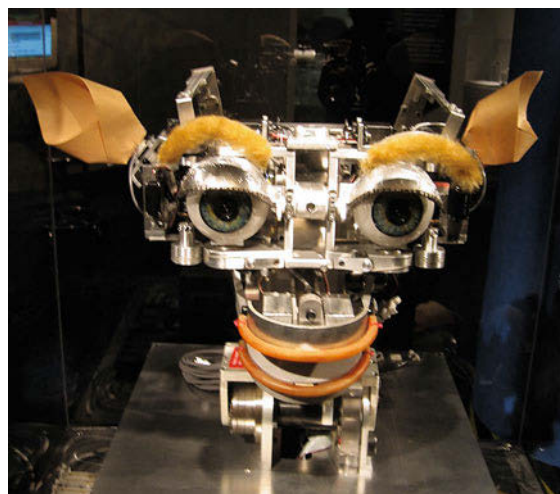


Fig. 71.4 Kismet's big round eyes and infant-like vocalizations are another example of the *baby schema* (courtesy of Šabanović)

perceptions of a robot's trustworthiness and its in-group membership. Researchers have also shown that roboticians themselves use cultural models unintentionally in their work, including particular models of emotional display [71.41], and cultural models reflecting historical, theological, and popular perceptions of robotic technology [71.42]. Research on cultural models in HRI not only points to the importance of reflexively including such models in robot design, but also allows researchers to do systematic research on culturally situated cognition using robots as stimuli.

Research on mental models applied to interactive robots has not only shown that people use their existing mental models to make sense of these novel artifacts, but also that we may need new *ontological*

categories to accommodate emerging mental models of these entities [71.16, 43]. Kahn's et al. [71.44] studies of children's moral interpretations of interactions with an AIBO robot showed that their mental models of the robots included rationalizations and behaviors related to both inanimate and animate objects. *Turkle* [71.45] suggests that interactive robots co-opting relational feelings and responses normally reserved for animals and humans call into question the authenticity of relationships. Further, *Turkle* [71.45] suggests that a more sophisticated new notion of autonomous yet inanimate artifacts has become necessary. Both researchers have suggested that interactive robots might comprise a new ontological category, and that we also need to be conscious of the ways in which interactions with these artifacts affect our mental models of animate beings.

71.1.2 Social Cognition

The development of robots that can interact naturally with humans calls for the detailed study of social activity and the cognitive models that underly such activities. *Scassellati* [71.46] argues that robots can help us study the limits of human social cognition because they are not alive, yet they can behave in socially appropriate (or inappropriate) and evocative ways. Robots that incorporate social cues such as gaze, proximity, and facial expressions, push our *Darwinian buttons* [71.16, p. 8] and effectively coerce us into interacting with them socially. Studying which cues have these effects is an opportunity to learn more about human social cognition and improve robot design.

Researchers studying the social aspects of cognitive HRI are identifying the minimal cues robots need to evoke social responses from people, including those related to robotic embodiment, gaze, proxemic cues, and interaction rhythms. Current research is also focused on applying and evaluating different models of cognition in the context of HRI. Robots can be unprecedented experimental tools for the study of social cognition. They can be used to provide stimuli in experiments and field studies, since their actions and behaviors can be carefully controlled, finely tuned and varied, and repeated exactly and indefinitely, which is often challenging even for well-trained human confederates [71.47, 48]. Furthermore, robots do not have difficulty acting *unnaturally* (e.g., not reacting to other person's cues) or violating social norms (e.g., being rude) when needed, a source of potential stress in human researchers [71.49].

Minimal and Human-Like Cues in HRI

One approach to studying social cognition has been to try to isolate the *minimal* set of cues that evoke social

responses and perceptions from human interaction partners. The creators of Muu followed a *minimal design strategy* [71.32], using cartoons and children's drawings to develop a robot that can be communicatively engaging to people without relying on overt human-likeness. *Kozima* et al.'s [71.50] *Keepon* was designed to include characteristics common to living beings, such as lateral symmetry and two eyes, which are assumed to be important for social interaction (Fig. 71.5). The robot also performs fundamental social behaviors, such as joint attention, eye contact, and emotional expression through bodily posture and movement and using only four degrees of freedom (Fig. 71.6). These minimal cues have been shown to be sufficient for engaging children in short-term interaction in the lab and long-term interaction in more natural environments, such as a classroom [71.50].

Studies with minimalist robots have also underscored the effect of *social context* in people's interpretations of robots. Field studies with *Keepon* in an elementary school showed that children incorpo-

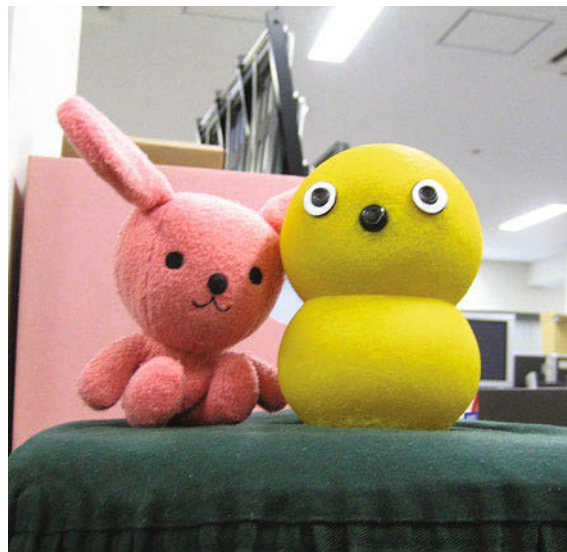


Fig. 71.5 *Keepon* is a simple robot used to investigate cues such as joint attention, emotive expression, and rhythmicity in HRI (courtesy of Šabanović)

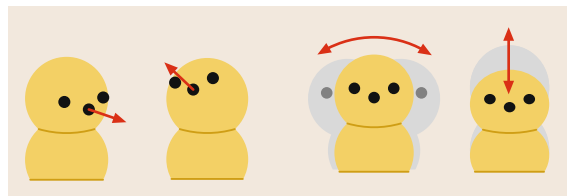


Fig. 71.6 *Keepon* uses four degrees of freedom to express emotive and attentional cues (after [71.50])



Fig. 71.7 An android robot fabricated by Kokoro Ltd. (courtesy of Šabanović)

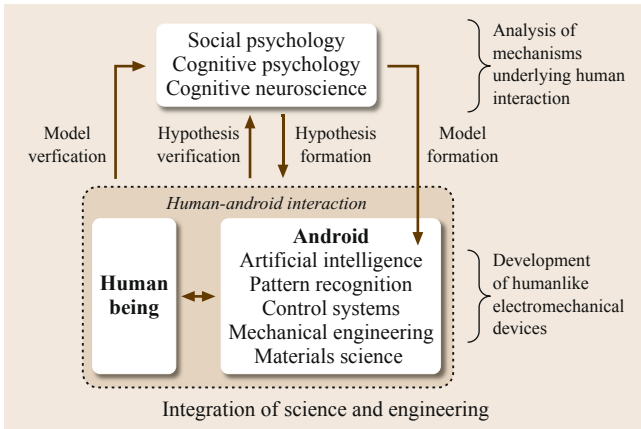


Fig. 71.8 Androids can be used to investigate human cognition analytically as well as synthetically (after [71.51])

rated the simple robot into a wide variety of interaction contexts (e.g., playing house with Keepon as

a baby or pet, or treating Keepon as another student in the classroom) due not only to its interpretive flexibility, but to the richness of the social environment. This inspired children to engage with the robot over long periods of time, sometimes years, whereas they became bored after 10–15 min when interacting with Keepon in the laboratory. The above mentioned Muu’s design was inspired by ecological models of cognition [71.52, 53] suggesting that a robot is inherently incomplete as a communicative device – it needs a human interaction partner to imbue its actions with meaning. Muu therefore relies on the context and the presence of other interactive agents (including people, other Muu, and objects such as blocks displayed in Fig. 71.3 for triadic interaction) to enable people to make sense of its actions and relationally ascribe social agency to the robot. The Social Trash-can project [71.54] similarly explored how minimal social cues, including contingent motion and approaching people, can be used to display the robot’s intentions to children and get their assistance in trash collection. Yamaji et al. [71.54] also showed that robots moving together as a group – relationally – were more successful in attracting the children’s attention than that moved individually.

An alternative approach to the study of social cognition through HRI focuses on *human-like realism* in appearance and behavior and is proposed by Ishiguro [71.47] and MacDorman and Ishiguro [71.48]. They claim that androids – robots that bear a close and sometimes *uncanny* resemblance to humans (Fig. 71.7, for example) – are unprecedented test beds for the study of social cognition. Used as stand-ins for humans in this *android science*, robots have a twofold function as experimental tools for evaluating hypotheses about human perception, cognition, and interaction, and as a testing ground for various cognitive models (Fig. 71.8). Using an android platform, Ishiguro [71.55] showed the importance of micro movements as a cue that incites people to attribute human-likeness to a robot in short (1–2 s) interactions. Another topic of continuing investigation is the possibility of simulating the personal presence of a remote actor in the local environment using an android platform [71.56, 57]. Shimada et al. [71.58] showed that people evaluated an android as more likable when it mimics them in a way similar to the *chameleon effect* that occurs when two people interact. MacDorman and Ishiguro [71.48] suggested that such androids can be used in research relating to a number of current topics of interest in cognitive science, including the mind-body problem, nature versus nurture, rationality and emotion in human reasoning, and the relationship between social interaction and internal cognitive mechanisms.

Embodied Social Cues

Embodiment separates robots from other interactive digital technologies and has been investigated through studies comparing how people interpret and act toward robots that are physically co-present with them and on-screen robots or social agents. Wainer et al.'s [71.59] comparison of people's interactions with an embodied robot and a simulated robot, and a co- and tele-present found that people were more engaged with, behaved more appropriately to, and anthropomorphized a co-located robot more than a tele-present robot. People interacting with an embodied robot have also shown tendencies to issue more commands than those interacting with a simulated robot [71.60]. The social effect of embodiment in HRI was further confirmed by Bainbridge's et al. [71.61] study showing that people are more likely to comply with requests made by an immediately present robot rather than requests made by a remote robot communicating with them through a television screen. These converging results strongly suggest that a robot's embodied presence has a significant cognitive effect on people's social responses to the robot. The embodied nature of robots also enables the study and use of various other social cues, including proxemic behaviors, gaze, and interaction rhythms, in HRI. A more detailed review of embodied social cues is provided by Mutlu [71.62].

Proxemic behaviors [71.63], the study of which is enabled by the embodied nature of robots, not only have a significant effect on people's perceptions of and behaviors toward robots, but have also been used as a measure of people's perceptions of robots as social agents. Takayama and Pantofaru [71.64] found that prior experience with pets and robots decreased the distance at which people felt comfortable around robots. Individual traits such as gender and personality also affect people's preferences regarding the distance at which they are comfortable with a robot approaching them [71.64, 65]. Proxemic behavior can be related to other social cues in complex ways. For example, Mumm's and Mutlu's [71.66] study showed that people will compensate for the intense gaze in their direction of a robot they do not like by moving away from the robot (Fig. 71.9). While most studies of proxemic systems have been done in the laboratory, recent work is also investigating more natural interactions between humans and robots in open environments [71.67].

Gaze is an important cue in human–human interaction and is also one of the most studied nonverbal social cues in HRI (👁️ VIDEO 128). People use many such seemingly unintentional, unconscious, and automatic nonverbal cues as clues regarding the mental states and intentions of other actors, including robots. Gaze has been shown to be useful for communicat-

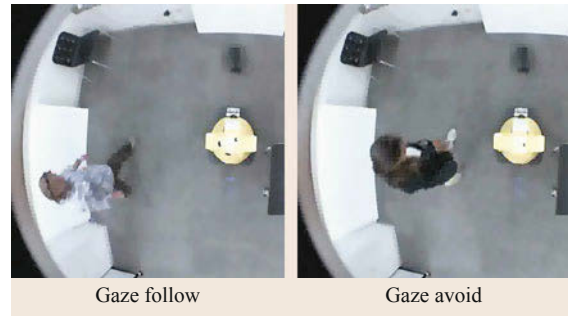


Fig. 71.9 In the study by Mumm and Mutlu [71.66], participants maintain a greater distance with the unlikable robot when the robot follows them with its gaze than when its gaze avoids the participant, while their proxemic behavior is not affected by a likable robot's gaze (courtesy of Mutlu)

ing intent, modulating interaction, and even affecting participants' experience and memory of the interaction. Researchers have shown that gaze can be used to engage users [71.69, 70] and to assign them particular roles in and manage the interaction [71.71]. A robot's gaze behavior can affect the human interaction partner's gaze and speech, their comprehension of the robot's speech [71.72], and people's memory of a story narrated by the robot and perceptions of the robotic storyteller [71.73]. Researchers studying the temporal aspects of gaze in HRI found that the timing of gaze behavior provides cues to human intentions while teaching the robot the names of objects, suggesting that properly timed gaze behaviors can have a positive effect on collaborative tasks between a human and a robot [71.68] (Fig. 71.10). Yu et al. [71.74] have developed a data-driven approach to analyzing human gaze in the context of HRI, which can be used

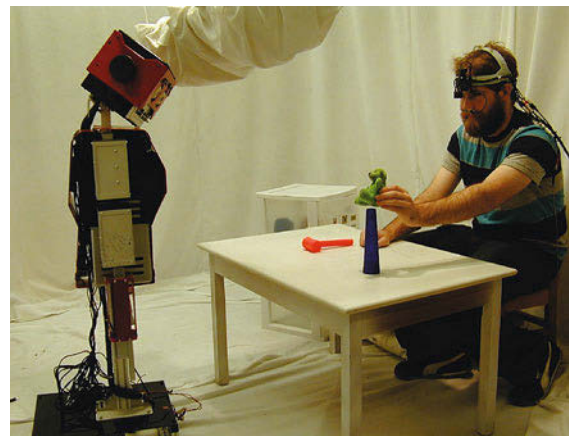


Fig. 71.10 Yu's et al. [71.68] HRI studies provide data for developing models of the temporal aspects of interaction (courtesy of Yu)

to develop detailed micro-behavioral gaze models that can guide robot behaviors as well as be used to understand human intentions and behaviors in the course of collaborative activities. A recent study by *Admoni et al.* [71.75], contrary to the assumption that anthropomorphic robots engage us automatically in much the same way we are engaged by people, shows that robot gaze is not necessarily treated by people in the same automatic way that human gaze is treated; we do not, therefore, necessarily perceive robots as social in an automatic and *mindless* way.

Interaction rhythms – nonverbal and largely unconscious temporal coordination between partners in an interaction – enable the exchange of information, anticipation of the interaction partner's actions, and even positive evaluations of interaction among humans as a fundamental subscript of all human interaction [71.76–78]. The rhythmicity of interaction is therefore also a crucial factor in *HRI*, both in terms of developing robots that can perceive and respond to people's rhythmicity, and of understanding how people react to the temporal aspects of robot behaviors. *Michalowski et al.* [71.79] used a dancing robot to explore the rhythmic properties of social interaction and showed that children were more likely to interact with a robot that was synchronized to background music rather than one that was not, and that the children's own rhythmic behavior was influenced by the robot's rhythmicity. In further research, *Michalowski et al.* [71.80] suggest that rhythmic interaction can be used as a form of play between children and robots, and that following the robot's lead in rhythmic entrainment with music causes children to attend more closely to musical rhythm. *Avrunin et al.* [71.81] found that simple changes in a robot's rhythmic dancing behavior, such as variation of motions, flaws in the robot's synchrony with music, and coordination of behavior changes with musical dynamics, increased people's perceptions of the robot's lifelikeness. *Hoffman and Breazeal* [71.82] used the temporal patterns of interaction – its rhythms – to develop robotic systems that can anticipate a human partner's actions in collaborative tasks, such as AUR, a robotic desk lamp, and Shimon, a marimba playing robot [71.83] ( VIDEO 236). Along with improving *HRI*, the use of robots in studying the rhythmic properties of interaction provides a new

tool for cognitive science research on these subtle, fine grained, and unconscious social cues.

Cognitive Development in *HRI*

A further topic of focus in cognitive *HRI* has been the study of social and cognitive development through studies of typically developing and autistic children's interactions with robots. Multiple studies in educational contexts have focused on understanding how children ascribe social agency to robots [71.12, 13]. *Kozima et al.* [71.50] found that children of different ages display varying modes of interaction with the robot, which suggest different levels of comprehension of its ontological status – 0-year-old interacted with *Keepon* as a moving thing, 1–2-year-old interacted with the robot as an autonomous system, and children over 2 years of age treated the robot as a social agent. *Deàk et al.* [71.84] studied the mechanism of joint attention in *HRI* to explore the importance of contingency and find out which perceptual features infants use to achieve shared attention by modeling these in a robot. Researchers also use robots to study social deficit disorders, particularly autism. Converging results on research using robots to study social deficit disorders show that autistic children respond to robots in a social manner that they do not display with people [71.85–87], inspiring researchers to perform studies with children in the context of *HRI*. One aim of such research is to try to understand which aspects of a robot's behavior enable autistic children to participate in social interaction, which may clarify some of the reasons for their difficulties when interacting with humans. *HRI* researchers have also applied robots to various therapeutic scenarios with autistic children in an effort to provide parents and therapists with a tool to improve communication and understand the children better [71.88, 89]. Studies by *Kozima et al.* [71.90] in which the robot *Keepon* interacts with children with autism suggest that such minimally designed robots can be used to motivate autistic children to share their mental states with others, such as therapists or parents. This work poses a promising possibility for learning more about social deficits and development disorders such as autism, as well as providing tools for diagnosis and therapy using robotic technologies.

71.2 Robot Models of Interaction

Simon [71.91] suggests that the study of human behavior can be approached through synthesis as well as analysis and designs computer simulations as a technique for understanding and predicting the behavior of

natural, social, and cognitive systems. In the spirit of *Simon's* synthetic approach to the study of human cognition, robotics researchers have been engineering robots as tools for developing and testing a variety of cog-

nitive, behavioral, and developmental models [71.47, 92, 93]. This approach assumes that cognitive models are validated when the implementation of a particular model on a robot produces behavior similar to that produced by humans in the same situation; if this does not occur, it is a sign that there may be something wrong with the model or the way it was implemented in the robot [71.46]. Cognitive HRI research involves the development of robotic platforms based on findings from cognitive science and using such platforms to extend knowledge about human cognitive processes.

71.2.1 Developmental Models

Robots are particularly appropriate for exploring theories of embodied and social cognition, which emphasize the centrality of the agent's interactions with its environment and other agents in that environment to cognitive functioning. In the process of synthesizing a robotic system, the researcher is drawn to focus on the dependency of cognition on noncognitive processes, including the social and physical environment in which cognition takes place. Robots such as Cog and Kismet [71.31] have been used to simulate and validate different theories of cognition, perception, and behavior. Cog was used to implement and test cognitive models relating to reaching behavior, rhythmic motor skills, visual search and attention, and social skill acquisition (e.g., joint attention and theory of mind). In the process they were able to validate, extend, and show the limitations of cognitive, behavioral, and developmental theories. In later projects, researchers have developed models inspired by human cognition and behavior such as social referencing [71.94], perception and action loops [71.95], anticipatory actions in collaborative teamwork [71.96], and others.

Robotics researchers apply the idea that the development of intelligence is embedded in social and cultural environment to the construction of robotic artifacts. For example, Breazeal [71.31] applied theories relating to infant social development, psychology, ethology, and evolution to design the robot Kismet, which used infant-like social cues to engage a human participant in interactions that would scaffold the robot's learning, as in the case of infant–parent interactions. Researchers have also developed a variety of robotic systems that exhibit cognitive traits such as imitation [71.97, 98], joint attention [71.99–101], and rhythmic synchrony [71.50, 102]. The Infanoid project [71.33] also used a synthetic approach in which development was understood through studying how the robot learns. Situated and embodied models have been applied to robot learning, particularly through imitation. For example, Bakker and Kuniyoshi [71.103] pro-

pose *imitation* as an interaction and learning paradigm in contrast to *robot programming* or *robot learning*. Further, they argue that robot programming is too hard and tedious to specify complex behaviors in sufficient detail and specify how they might be adapted to novel situations.

71.2.2 Robot Spatial Cognition

Systems dedicated to modeling spatial language and interaction, including the theories by Jackendoff [71.104], Landau and Jackendoff [71.105], and Talmy [71.106], have been produced for many years. Several previous works have been computational instantiations of the ideas presented in these theories, in particular the implementation and testing of spatial semantics models. Regier [71.107] built a system that assigns labels, such as *through* to a movie showing a figure moving relative to a landmark object. Kelleher and Costello [71.108] and Regier and Carlson [71.109] built models for the meanings of static spatial prepositions, such as *in front of* and *above*.

Many authors have proposed formalisms for enabling systems to reason about the semantics of natural language use in the context of giving directions. For example, Bugmann et al. [71.110] identified a set of 15 primitive procedures associated with clauses in a corpus of spoken natural language directions. Levit and Roy [71.111] designed *navigational informational units* that break down instructions into components. MacMahon et al. [71.112] represented a clause in a set of directions as a compound action consisting of a simple action (move, turn, verify, and declare-goal), plus a set of pre- and post-conditions. Many of these previous representations are expressive but difficult to automatically extract from text. Some authors avoid this problem by using human annotations [71.111, 112] or by specifying the robot's behavior in a controlled language [71.113]. Matuszek et al. [71.114] created a system that follows directions using a machine translation approach. Similarly, Vogel and Jurafsky [71.115] used reinforcement learning to automatically learn a model for understanding route instructions.

71.2.3 Symbol Grounding

Mapping language from the human partner to aspects of the external world – locations, objects, or actions the robot should take – described by the language was referred to as an instance of the *symbol grounding* problem [71.116]. There are three different ways people have approached the symbol grounding problem, which is more general than spatial cognition, in robotics. Starting with Winograd [71.117], many have created symbol

systems that map between some language and the external world by manually connecting each term onto a pre-specified action space and set of environmental features [71.110, 112, 113, 118–121]. This class of systems takes advantage of the structure of linguistic interaction, but the systems usually do not involve learning, have little perceptual feedback, and have a fixed action space. A second approach involves learning the meaning of words in the sensorimotor space (e.g., joint angles and images) of the robot [71.122–124]. By treating human interaction terms as sensory input, these systems must learn directly from complex features extracted by perceptual systems, resulting in a limited set of commands that can be robustly understood. A third approach is to use learning to convert from an interaction onto aspects of the environment. These approaches may only use linguistic features [71.125, 126], spatial features [71.107] or linguistic, spatial, and semantic features [71.114, 115, 127–129]. These approaches learn the meaning of spatial prepositions (e.g., *above* [71.107]), verbs of manipulation (e.g., *push* and *shove* [71.130]), and verbs of motion (e.g., *follow* and *meet* [71.131]) and landmarks (e.g., *the doors* [71.129]).

Recent progress in probabilistic relational models, such as the generalized grounding graph (G^3), has addressed these issues by exploiting the structure of

spatial discourse, breaking down a natural language command into component clauses and connecting each word to a physical interpretation [71.131, 132]. The grounding graph takes full advantage of the hierarchical and compositional structure of natural language commands and is able to ground landmarks, such as *the computers*, by exploiting object co-occurrence statistics between unknown noun phrases and known perceptual features, spatial relations, such as *past* in the path of an agent relative to an object, and motion verbs, such as *follow*, *meet*, *avoid*, and *go* in the path of a single agent or multiple agents. Once trained, the G3 model can ground spatial discourse in a semantic map of the environment; the map can be given a priori or created on the fly as the robot explores the environment. The G3 model is dynamically instantiated as a hierarchical probabilistic graphical model that connects each element in a natural language command to an object, place, path, or event in the environment. Its structure is created according to the compositional and hierarchical structure of the command, learning the mapping from language onto a continuous robot plan. The G3 model is trained on a corpus of natural language commands paired with groundings, and learns meanings for words and phrases in the corpus, including complex verbs, such as *put* and *take*.

71.3 Models of Human–Robot Interaction

Robotic technologies that interact with people – whether they afford closed-loop teleoperation or collaborate autonomously as peers – need to interpret, make decisions about, and respond to their environment, particularly the physical world, the task that they are expected to support, and the actions, goals, and intentions of the other agents – including people. To achieve these goals, robots need *models* that accurately represent the physical and cognitive characteristics of their environment. These models might outline such characteristics as narrowly as control–action relationships in the context of teleoperation or as comprehensively as human–robot joint activity in the context of peer-to-peer collaboration. Cognitive HRI considers the

robotic system to be a part of a distributed cognitive system and therefore seeks primarily to develop cognitively inspired models [71.2]. These models might draw on knowledge about human cognition to improve the usability of robotic system, mimic human decision making or behavior mechanisms, or represent the complete human–robot cognitive system, offering cognitive representations for different paradigms of HRI (Fig. 71.11).

71.3.1 Dialog-Based Models

Research on human robot interaction across different interaction paradigms from teleoperation [71.133, 134]

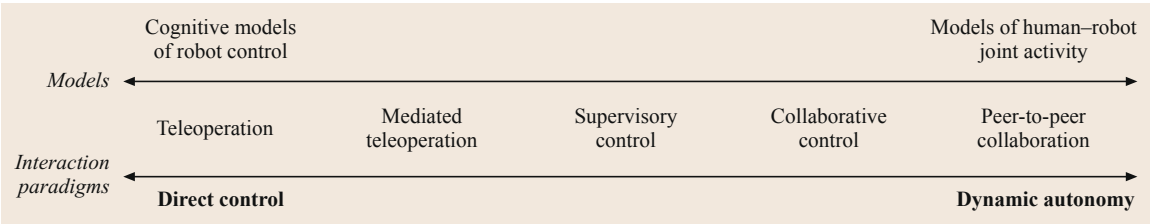


Fig. 71.11 Different paradigms of HRI (after [71.2])

to peer-to-peer interaction [71.135] has highlighted the need for establishing *common ground* [71.136] for effective HRI. In the context of teleoperation, Burke et al. [71.133] found that a lack of appropriate shared representations among human team members and the robot resulted in discrepancies in understanding among team members and breakdowns in perceiving and interpreting data provided by the robot. Stubbs et al. [71.134] observed such lack of common ground between operators and the robot across varying levels of autonomy. In the context of peer-to-peer interaction, Kiesler [71.135] argues that participants in an encounter seek to minimize their collective effort to reach mutual understanding and that the effort needed to establish this understanding between a robot and its users might determine the outcomes and success of HRI. These examples have motivated a large body of research in developing dialog-based models for establishing common ground in human–robot joint activity.

An example of the application of a dialog-based model to a task domain that traditionally involved supervisory control is Fong's et al. [71.136] *collaborative control* system. In this system, the human and the robot collaborated as partners to perform tasks such as navigation, collaborative exploration, and multirobot teleoperation and achieve shared goals within these tasks. The interaction between the robot and its human counterpart involved engaging in dialog to share information and control at key points in the task. For instance, when the robot encountered an obstacle, it asked the user, *Can I drive through <image>?* along with an image of the obstacle. In asking these questions, the robot drew on specific attributes of the user, such as response accuracy, expertise, availability, efficiency, and preferences to determine whether or not it should direct specific questions to its user.

A number of proposed models and systems take the dialog-based interaction paradigm further to involve the robot and its human counterpart jointly addressing the domain task and dialog itself as *joint action* [71.137, 138]. In this peer-to-peer setup, either party selects goals to address and strategies to be used to address them and either party performs any part of the task. The model proposed by Foster et al. [71.137] includes a semantic interpretation module and a central decision-making module which draw on resources, such as a history of the ongoing discourse between the robot and its user, a world model, a domain planner, and a representation of the plan that is currently being executed, in order to generate action and communication behaviors.

The model proposed by Li et al. [71.138] draws on joint intention theory [71.139], considering the joint activity to involve a common persistent goal of achieving conversational grounding, and explicitly uses elements

of grounding in representing conversational contributions. These contributions involve a *presentation* and an *acceptance* phase. For example, when an agent asks a question and the other agent answers, the question becomes the presentation and the answer becomes the acceptance, forming a *grounded exchange*. The model considers exchanges that involve a presentation without an acceptance to be *ungrounded*. Discourse contributions take place at two layers: *intention* and *conversation*. At the intention layer, the system plans communication intentions based on analyses of previous discourse and the robot's control system. These intentions can be *self-* or *other-motivated* for each agent. The conversation layer involves the articulation of communication intentions through verbal and nonverbal behaviors. The two layers form an *interaction unit (IU)* in the model. The model determines whether an IU is presentation or acceptance and whether it is grounded or ungrounded by assessing whether it satisfies joint intentions of the agents. Figure 71.12 illustrates how an other-motivated exchange is assessed by the model to determine whether the exchange is a presentation or an acceptance.

Models of Situated Human–Robot Dialog

The models and systems described above consider task-based and communicative exchanges in HRI as a dialog and extend models of spoken dialog to accommodate requirements that are specific to HRI, such as task-management, mixed-initiative dialog management, and physically situated referencing. Research in cognitive HRI has also explored the development of dialog systems that explicitly integrate these mechanisms into dialog modeling and the development of specific models and mechanisms for these requirements.

An example of dialog systems that are specifically developed for situated human–robot dialog is the pattern-based mixed-initiative (PaMini) HRI framework [71.140]. This framework extends spoken dialog systems with two key components: a task-state protocol and interaction patterns. The task-state protocol component explicitly defines *tasks* that either the robot's perceptual or control subsystems can perform. A task is defined as an execution state and preconditions for execution. The task-state protocol specifies task states and transitions among them to support coordination. The interaction patterns component provides high-level representations of recurring dialog structures such as a *clarification*. A comparison of most commonly used spoken dialog systems and the PaMini framework in the context of a human–robot situated learning scenario is provided by Peltason and Wrede [71.141].

Another example is the Robot Behavior Toolkit developed by Huang and Mutlu [71.3], which supports

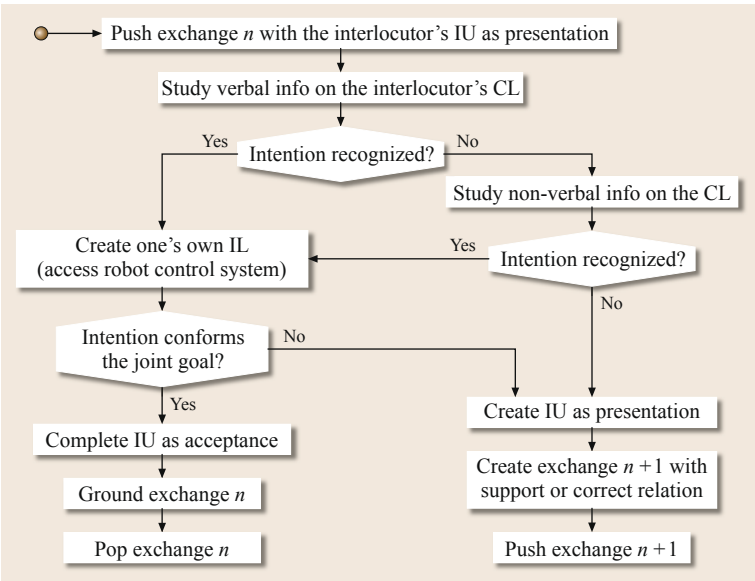


Fig. 71.12 The model evaluates an exchange provided by the interaction partner to determine its *presentation* or *acceptance* status and determine an appropriate action (after [71.138])

situated human–robot dialog by integrating nonverbal cues for task-based referential communication and conversation into the robot’s speech. This system uses a *repository* of specifications of situated communication cues based on models of human interactions and an *activity* model (described in more detail below) that specifies the joint human–robot activity including the agents, task context, shared task goals, and expected

task outcomes to integrate the situated communication cues that are expected to support these outcomes into the robot’s speech. Figure 71.13 displays an example behavior generated by the Toolkit in a collaborative manipulation task. An evaluation of their system showed that interactions in which the robot displayed these situated communication cues as directed by the system more effectively supported desired task outcomes compared with baseline interactions (VIDEO 128).

Research in cognitive HRI has also explored the development of models for specific communication and coordination mechanisms in situated interaction, such as perspective-taking, spatial referencing, reference resolution, and joint attention (VIDEO 129).

Perspective-Taking. A core process in situated interaction toward establishing common ground is *perspective-taking* [71.142]. Research in social cognition has shown that the ability to take another’s perspective and share common ground significantly improves collaborative performance in human teams [71.143]. Research in HRI has also explored how robots might employ this core mechanism to establish common ground with their users in situated interactions and has proposed several models that supported perspective taking.

Trafton et al. [71.144] studied interactions among astronauts in a naturalistic collaborative assembly task and found that a quarter of the utterances in the data involved taking the perspective of another and that participants frequently switched among egocentric, exocentric, addressee-centered, and object-centered perspectives. Based on their results, they developed a cog-

```
<behaviors>
<channel type='gaze'>
  <action endTime='214.5' startTime='0' target='unspecified' />
  <action endTime='1160' startTime='214.5' target='the green
    object with one peg' />
  <action endTime='2735.4' startTime='1160' target='unspecified' />
  <action endTime='3597' startTime='2735.4' target='the red box' />
  <action endTime='4308' startTime='3597' target='unspecified' />
  <action endTime='4963' startTime='4308' target='listener' />
</channel>
<channel type='speech'>
  Could you help me put the green object with one peg into the red
  box, please?
</channel>
</behaviors>
```

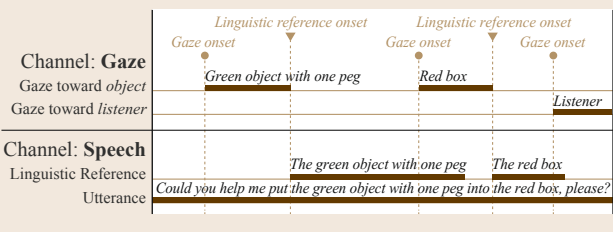


Fig. 71.13 The robot behavior toolkit uses specifications from a repository and a model of the joint activity to integrate effective multimodal task-related dialog behaviors (after [71.3])

nitive model of perspective taking that allowed the robot to maintain multiple perspectives – or *alternative worlds* – at once and explore propositions about these worlds, such as the perspective of an interaction partner. This exploration allowed the robot to make inferences about the perspective of its partner by simulating this alternative world and act on the world from this perspective. The following sequences of actions illustrate the simulations that the robot might carry out based on the command *go to the cone* (adapted from Trafton et al. [71.2]). Underlined text describes components of the system implementation:

Simulate current real world (i. e., perceive it)

Perception specialist notices the existence and location of *person*, *cone₁*, *cone₂*, and *obstacle*
Language specialist hears *Coyote*, *go to the cone* and infers that there is an object, *C*, that is a cone and that the *person* wants it to go to
Identity hypothesis specialist infers that *C* can be identical to *cone₁* or *cone₂*
 $C = \text{cone}_1, C = \text{cone}_2$
Identity constraint specialist notices a contradiction
 This contradiction triggers the counterfactual simulation strategy

Simulate the world where $C = \text{cone}_1$

Because in this world *person* has referred to *cone₁*, the perspective-simulation strategy is triggered

Simulate the world where $C = \text{cone}_1$ and *robot* = *person*

The spatial reasoning perspective indicates that *cone₁* does not exist in this world because *person* cannot see it
 Thus, $C \neq \text{cone}_1$

Simulate the world where $C = \text{cone}_2$

Because in this world *person* has referred to *cone₂*, the perspective-simulation strategy is triggered

Simulate the world where $C = \text{cone}_2$ and *Robot* = *Person*

Because *cone₂* is visible in this world, there is no contradiction in this world
 Infer that $C = \text{cone}_2$ (i. e., the *cone* refers to *cone₂*)

Following a *counterfactual simulation strategy* provides the robot with the ability to make inferences about situated actions across alternative scenarios with alternative physical (e.g., whether or not an object is present) and cognitive (e.g., whether or not the object is visible to the human counterpart) characteristics and determine appropriate next actions, such as carrying out a request or seeking clarification from its human counterpart.

Figure 71.14 illustrates four alternative scenarios with different physical and cognitive properties explored by Trafton et al. [71.144]. In each scenario, the robot assesses these properties to determine its next actions, as illustrated below.

Algorithm 71.1

```

function: Scenario( $n\text{Cones} = 1 \Rightarrow \text{cone}_a$ )
if  $\text{cone}_a = \text{visible}_{\text{robot}} \wedge \text{cone}_a = \text{visible}_{\text{human}}$  then
  Go to  $\text{cone}_a$ 
end if
function: Scenario( $n\text{Cones} = 2 \Rightarrow \text{cone}_a, \text{cone}_b$ )
if  $\text{cone}_a, \text{cone}_b = \text{visible}_{\text{robot}} \wedge \text{cone}_a = \text{visible}_{\text{human}}$  then
  Go to  $\text{cone}_a$ 
end if
function: (Scenario( $n\text{Cones} = 1 \Rightarrow \text{cone}_a$ ))
if  $\text{cone}_a, \text{cone}_b \neq \text{visible}_{\text{robot}} \wedge \text{cone}_a = \text{visible}_{\text{human}}$  then
  Check hidden location
end if
function: Scenario( $n\text{Cones} = 2 \Rightarrow \text{cone}_a, \text{cone}_b$ )
if  $\text{cone}_a, \text{cone}_b = \text{visible}_{\text{robot}} \wedge \text{cone}_a,$ 
    $\text{cone}_b = \text{visible}_{\text{human}}$ 
then
  Request clarification
end if
  
```

Berlin et al. [71.145] developed a similar model that enabled the robot to understand its environment from the perspective of an interaction partner by maintaining

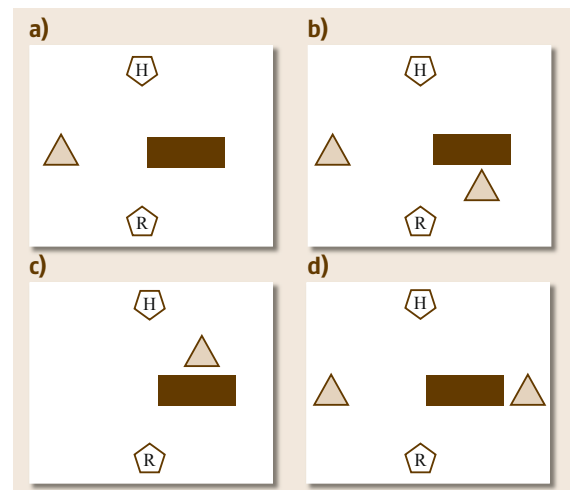


Fig.71.14a–d The alternative scenarios considered by the system in which the robot and its human counterpart are in a room with several objects and possible occlusions from the perspectives of the robot or the human (after [71.144])

separate and potentially different sets of beliefs in its belief system for itself and for its interaction partner. To construct a model of the beliefs of its interaction partner, the robot employed the same mechanisms it used to model its own beliefs but transformed the data it perceived from the world to match the reference frame of its interaction partner. These two sets of beliefs were maintained separately so that the robot can compare differences between its beliefs and its interaction partner's beliefs and plan actions in order to establish common ground or identify discrepancies in its learning in the context of task learning. Figure 71.15 illustrates parallel beliefs maintained by the robot in a button-pressing task.

Spatial Referencing. Moratz et al. [71.146] proposed a cognitive model of spatial reference that represented different kinds of spatial reference systems and allowed the robot to interpret instructions from an interaction partner. This model mapped the locations of all objects as projections on a plan view, considering the robot's point of view as *origin* and the location of the object that will be used as *relatum* to determine the reference axis. This axis enabled the robot to interpret directions such as *left of*, *right of*, *in front of*, and *to the back* in relation to the relatum, providing the robot the ability to interpret natural language references to objects in the environment.

Reference Resolution. Ros et al. [71.147] extended these approaches to develop a model that enabled the robot to clarify references made by its interaction partner. This model employed several mechanisms including visual perspective taking, spatial perspective taking, symbolic location descriptors, and feature descriptors to determine whether it needed any clarification on its interaction partner's references. The visual perspective taking mechanism allowed the robot to determine whether or not objects in the environment were in its interaction partner's focus of attention (FOA), in its part-

ner's field of view (FOV), or out of its partner's field of view (OOF). The spatial perspective taking mechanism maintained egocentric and addressee-centered perspectives to determine ambiguities in object references. The system also included symbolic location descriptions such as *is in*, *is on*, and *is next to* to determine spatial relationships between objects and the environment. Finally, the robot used feature descriptors such as color and shape to identify ambiguities in the references of its interaction partner. Once the robot determined the need clarification in its partner's references, it used an ontology-based clarification algorithm to ask questions to its partner about the object of reference.

Joint Attention. Another key mechanism in situated interaction is *joint attention* – the ability to use non-verbal cues, such as gaze and pointing, to establish common ground on what referents in the environment are under consideration in the dialogue [71.149]. Scassellati [71.99] proposed a task-based decomposition of joint attention skills, including mutual gaze, gaze following, imperative pointing, and declarative pointing, and implemented these skills in a robot as stages for establishing joint attention with a human counterpart. The mutual gaze skill provided the robot with the ability to recognize and maintain eye contact with its interaction partner. At the gaze following stage, the robot followed the eyes of its partner to direct its attention to the object of its partner's attention. Imperative pointing involved pointing at an object that is out of reach in order to request the object. Finally, the declarative pointing stage involved extending an arm and index finger to draw attention to an object that is out of reach without necessarily requesting the object.

Connection Events. Rich et al. [71.150] argued that mechanisms such as joint attention serve as *connection events* in situated dialog and establish and maintain engagement among interaction partners. From data on human interactions, they identified a set of key connec-

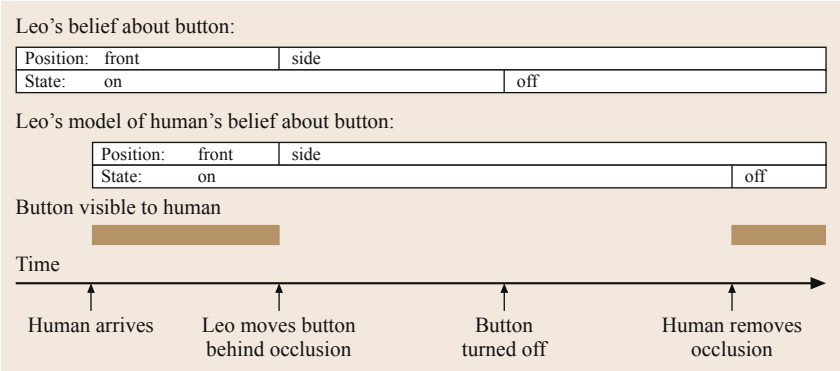
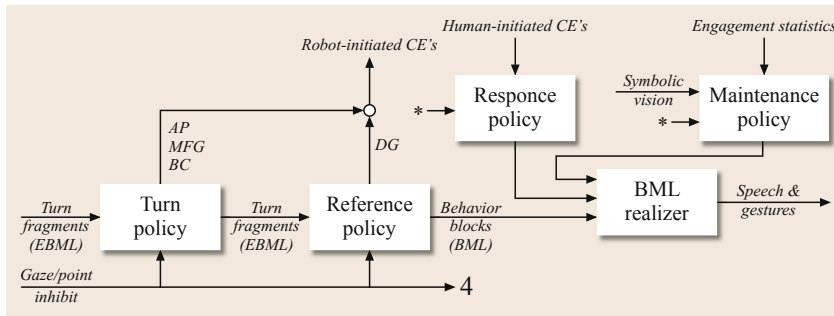


Fig. 71.15 In the system proposed by Berlin et al. [71.145], the robot maintains a parallel beliefs for itself and for its human counterpart for the task and updates its beliefs based on sensory input and those of the user based on the user's awareness (after [71.145])



tion events, including mutual gaze, directed gaze, adjacency pairs, and backchannels, and developed a system that recognized these events in human counterparts and generated them for a robot (see *Rich et al.* [71.150] for details on the recognizer and *Holroyd et al.* [71.148] for details on generation). The recognizer module included dedicated recognizers for each type of connection event and an estimator for engagement levels for the robot's human counterpart, while the generation module included four policy components and a behavior mark-up language (BML) realizer for generating robot behaviors toward establishing and maintaining engagement. The components of this engagement generator are illustrated in Fig. 71.16.

71.3.2 Simulation-Theoretic Models

Research in cognitive HRI has also been inspired by neurocognitive mechanisms in developing models of human-robot joint activity, building particularly on *simulation theory*, which suggests that people (and primates) represent other people's mental states by adopting their perspective, specifically by tracking or matching their states with resonant states of their own [71,151]. This simulation-theoretic approach led to several models of robot behavior and human-robot joint action that involve the robot imitating or simulating the behaviors of its interaction partner in order to learn from or make inferences about its partner's goals.

As an example of this approach, *Bicho et al.* [71, 152] proposed a model for action preparation and decision-making in cooperative human-robot tasks that is inspired by the finding that action observation elicits an automatic activation of motor representations associated with the execution of the observed action. This *motor-resonance mechanism* allows people to internally simulate action consequences using their own motor repertoire and predict the consequences of action of others. In the proposed model, a perception-action linkage enables efficient coordination of actions and decisions between the agents in a human-robot joint action task.

The model integrates a mapping between observed actions and complementary actions in memory, while taking into account the inferred goals of the actions of the interaction partner, contextual cues, and shared task knowledge.

Building on simulation theory, *Gray et al.* [71.153] proposed a similar system in which the robot parses user actions and matches the user's movements to movements in its own repertoire toward making inferences about the user's goals and perform a task-level simulation (Fig. 71.17). This simulation allows the robot to determine the preconditions of the schemas that represent the task and track its human partner's progress over the course of the task in order to anticipate its partner's needs and offer relevant help accordingly. The simulation also provided the robot with the ability to make inferences on the beliefs of its partner and simulate its partner's perspective in a fashion similar to the perspective-taking mechanisms proposed by *Trafton et al.* [71.144] and *Berlin et al.* [71.145] ( VIDEO 130).

Aspects of the simulation-theoretic approach explicitly taken in these examples can also be seen in other control architectures developed for [HRI](#). [Nicolescu and Mataric](#) [71.154] proposed a control architecture that unifies perception and action to achieve *action-based*

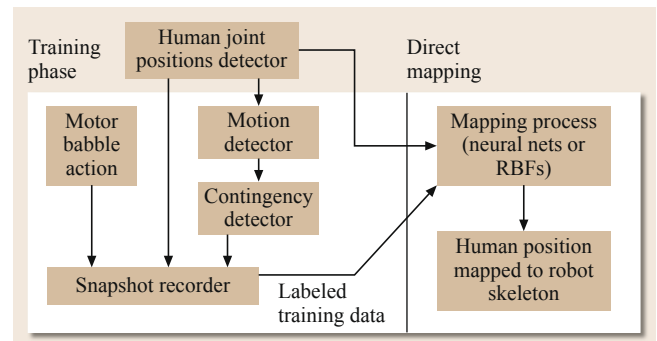


Fig. 71.17 The mapping of perceived human actions onto the robot's body in order to make comparisons and task-level inferences (after [71.153])

interaction. In this architecture, behaviors are built from *perceptual* and *active* components. Perceptual components allow the robot to link its observations and actions and thus to learn to perform a task from the experiences it gains from its interactions with people. Active components enable task-based behaviors that also serve as implicit communication rather than explicit behaviors such as speech and gestures. Behavior representation in the architecture captures two types of behaviors: *abstract* and *primitive*. Abstract behaviors are explicit specifications of the behaviors' activation conditions (preconditions), goals in the form of abstracted environmental states, and effects (postconditions), while primitive behaviors are those that the robot performs to achieve these effects. By linking perceptions and actions, the robot learns what actions of its own might achieve the same observed effects.

71.3.3 Intention- and Activity-Based Models

The models and systems described above are concerned primarily with establishing and maintaining common ground and coordinating actions in task-based interactions using dialog- and simulation-theoretic approaches with limited consideration of the broader context of these interactions as complex activities involving multiple agents with common goals and commitments to these goals. A number of models and systems sought to address this limitation, building on models and theories of human joint activity such as joint intention theory [71.139] and activity theory [71.7].

Building on joint intention theory, Breazeal et al. [71.155] proposed a model of human-robot collaboration that involved dynamically meshing subplans into joint activity toward achieving common goals of the human-robot team. In this model, task and goal representations have a goal-centric view, employing an action-tuple data structure that captures preconditions, executables, until-conditions, and goals. Tasks are represented in a hierarchical structure of actions and recursively defined subtasks. Goals are also represented hierarchically as overall intent rather than a chain of low-level goals. The implemented joint intention model dynamically assigns tasks to members of the human-robot team. These intentions are derived based on the robot's actions and abilities, the actions of the human partner, the robot's understanding of the common goal of the team, and its assessment of the current task state. At every stage of the interaction, the robot negotiates who should complete the task. Action at these points might look like turn-taking or simultaneous action (the robot and the human working on different parts of the task).

Alami et al. [71.156, 157] similarly built on joint intention theory to propose a human-robot decision framework in which team members are committed to a *joint persistent goal* and follow cooperation schemes to contribute toward achieving this goal. The framework involves a goal planner called *the agenda* for the robot and human collaborators to pursue, a proxy representation of the human in the robot called *Interaction Agents (IAA)*, *task delegates* that monitor and control the task commitment of the human or the robot for each active, inactive, or suspended goal, and a *robot supervision kernel* that monitors and controls robot activities. For each new active goal, the Robot Supervision Kernel creates a Task Delegate, selects or elaborates a plan, and allocates the roles of each team member.

Fong et al. [71.1] proposed a similar system called the *HRI operating system (HRI/OS)* to support human-robot teamwork. The system involves a task manager, resource manager, interaction manager, spatial reasoning agent, context manager, human and robot agents, and an open agent architecture (OAA) facilitator. The task manager decomposes the overall goal of the system into high-level tasks and assigns to humans or robots for execution. The manager relies on the agents to complete the low-level steps of the tasks. It communicates with the Resource Manager to find an agent capable of performing the work. Resource manager processes all agent requests, prioritizing the list of agents to be consulted when a task needs to be performed. Interaction manager coordinates dialog-based communication between agents. Context manager keeps track of everything that occurs while the system is running including task status and execution, agent activities, agent dialogue, etc. Spatial reasoning agent (SRA) is used to resolve spatial ambiguities in human-robot dialog through mechanisms such as perspective taking and frames of reference, resolving ambiguities among as ego-, addressee-, object-, and exo-centric references. To do this, SRA transforms the spatial dialog into a geometric reference and perform a *mental simulation* of the interaction to explore how ambiguities might be resolved through multiple references. Finally, the OS includes a software representation of the human – a human proxy agent that represents user capabilities and accepts task assignments in the way that robot agents do. These proxies represent task capabilities, including domains of expertise, and provide health monitoring feedback.

Huang and Mutlu [71.3] built on an alternative model of human activity – activity theory [71.7] – to develop a model of human-robot joint activity. Their model builds on five key constructs from activity theory including consciousness, object-orientedness, hierarchical structure, internationalization and external-

ization, and mediation. The *consciousness* construct pertains to attention, intention, memory, reasoning, and speech and includes specific representations for attention and intention. The *object-orientedness* construct describes material artifacts, plans of action, or common ideas to be shared by the members of the joint activity. Following the *hierarchical structure* construct, the model organizes joint activity into three layers: activity, action, and operation. An activity consists of a series of actions that share the same goal, and each action has a defined goal and a chain of operations that are regular routines performed under a set of conditions. *Internalization and externalization* describes cognitive processes; internalization involves transforming external actions or perceptions into mental processes, while externalization is the process of manifesting mental processes in external actions. Finally, the *mediation* construct defines several external and internal tools, such as physical artifacts that might be used in an activity and cultural knowledge or social experience that an individual might have acquired, as mediators of human–robot joint activity. These constructs and their corresponding system elements allow the construction of and planning for joint human–robot activities. For each activity, a *motive* governs actions. Each action, by achieving its corresponding goal, helps to fulfill the motive of the activity. Each action may have several *operations* that are constrained by a set of conditions and that can be executed only when all the conditions are met. Actions have predefined *outcomes*, which specify the orientation of an action. Figure 71.18 shows the XML (extensible markup language) representation of a model of a collaborative manipulation task.

71.3.4 Models for Action Planning

The models described above primarily enable communication and coordination between humans and robots toward planning and carrying out joint tasks. In order to successfully contribute to these tasks, robots also need models for planning their actions in a dynamic physical and cognitive environment. Research in cognitive HRI seeks to develop models for *action planning* that help robots estimate the actions that they have to take in order to achieve task goals and learn the parameters of the tasks space. The paragraphs below review research in two common approaches to building such models: *decision-theoretic models* and *model learning*.

Decision–Theoretic Models

One of the simplest approaches to control and decision-making in HRI is to define the interaction as a decision-theoretic planning problem, such as a Markov decision process (MDP). Formally, an MDP consists of the n-

tuple $\{S, A, T, R, \gamma\}$. The set S is a set of states, which in the HRI setting typically correspond to the combination of state variables, such as the robot state and the desired outcome of the interaction. For example, if the interaction model allows a human partner to instruct the robot to move to different locations in the environment, one state variable may correspond to different current locations of the robot and another state variable may correspond to the goal states intended by the human partner. The full state space S is given by the combination of possible values for the different state variables.

The action set A represents actions that the robot may take. The actions may include asking a question, performing some physical movement, or even doing nothing. Each action has a cost R depending on the current state, which rewards the robot for performing useful actions, and penalizes the robot for taking actions that either make no immediate progress toward the specified goal (typically a small penalty) or completely unhelpful (a large penalty).

Lastly, the transition function T provides a notion of the dynamics of the environment in terms of how the state changes as robot takes actions, and especially how a human partner's state variables may change as the robot takes actions. The transition function $T(s'|s, a)$ places a probability distribution over the states to which the user in state s may transit if the robot takes action a . The MDP formulation is very appealing, because there exist efficient techniques for solving for interaction policies. Once the policy is computed, the interaction can be managed simply by querying the policy for the

```
<Activity id='1'>
  <Motive>clear(table)</Motive>
  <Description>Clear objects on table</Description>
  <Participants>Self, User1</Participants>
  <Action id='1'>
    <Outcome>Task</Outcome>
    <Goal>disappear(object)</Goal>
    <Description>
      Instruct User1 to categorize object
    </Description>
    <Operation type='utterance'>
      <Condition>present(User1)</Condition>
      <Condition>
        known(the blue object with two pegs)
      </Condition>
      <Condition> known(the blue box)</Condition>
      <Info turn='end'>
        Could you help me put the blue object with
        two pegs into the blue box, please?
      </Info>
    </Operation>
  ...
</Action>
</Activity>
```

Fig. 71.18 The XML representation of the activity-theory-based model for a collaborative manipulation task (after [71.3])

appropriate action in response to the current state of the robot and the human partner.

A limitation of the MDP approach is that some of the state variables may not be directly observable, in particular the state variables corresponding to human intentional states, such as intended goal locations of the robot. The values of the state variables must be inferred from observations, such as speech acts performed by the human partner, which are inherently noisy. For example, the system may hear the words *coffee machine* when the user asks the robot to go to *copy machine*. While speech recognition errors may be mitigated to some extent by asking the user to use only acoustically distinct keywords when speaking to the system, a system that does not model the likelihood of recognition errors and act accordingly will be brittle; a robust system must be able to infer user intent under uncertainty.

The observations are rarely sufficient to uniquely determine the current state, but more commonly are used to compute a *belief*, or probability distribution over dialog states. If the agent takes some action a and hears observation o from an initial belief b , it can easily update its belief using Bayes rule

$$b^{a,o}(s) = \frac{\Omega(o|s', a) \sum_{s \in S} T(s'|s, a)b(s)}{\sum_{\sigma \in S} \Omega(o|\sigma, a) \sum_{s \in S} T(\sigma|s, a)b(s)} . \quad (71.1)$$

This probability distribution will evolve as the dialog manager asks clarification questions and receives responses. In Fig. 71.19, we show a cartoon of a simple dialog model. Initially, we model the user as being in a *start* state. Then, at some point in time, the user speaks to the robot to indicate that he or she wants it to perform a task. We denote this step by the set of vertical stack of nodes in the center of the model. Each node represents a different task. The dialog manager must now interact with the user to determine what is wanted. Once the task is successfully completed, the user transitions to the right-most *end* node, in which he or she again does not desire anything from the robot. We note that it can be easily augmented to handle more complex scenarios. For example, by including the time of day as part of the state, we can model the fact that the user may usually wish to go to certain locations in the morning and other locations in the afternoon.

Intuitively, we can see how the belief can be used to select an appropriate action. For example, if the dialog manager believes that the user may wish to go to either the coffee machine or the copy machine (but not the printer), then it may ask the user for clarification before commanding the wheelchair to one of the locations. More formally, we call the mapping from beliefs

to actions a policy. We represent this mapping using the concept of a value function $V(b)$. The value of a belief is defined to be the expected long-term reward the dialog manager will receive if it starts a user interaction in belief b . The optimal value function is piecewise-linear and convex, so we represent V with the vectors V_i ; $V(b) = \max_i V_i \cdot b$. The optimal value function satisfies the Bellman equation [71.158]

$$V(b) = \max_{a \in A} Q(b, a) ,$$

$$Q(b, a) = R(b, a) + \gamma \sum_{o \in O} \Omega(o|b, a) V(b_a^o) , \quad (71.2)$$

where $Q(b, a)$ represents the expected reward for starting in belief b , performing action a , and then acting optimally. The belief b_a^o is b after a Bayesian update of b using (71.1), and $\Omega(o|b, a)$, the probability of seeing o after performing a in belief b ($\sum_{s \in S} \Omega(o|s, a)b(s)$).

There are also non-Bayesian approaches for acting in uncertain environments. Many interaction systems provide the dialog manager with a set of rules to follow given particular outputs from a speech recognition system. The drawback to rule-based systems is that they often have difficulty managing the many uncertainties that stem from noisy speech recognition or linguistic ambiguities. The ability to manage the trade-off between gathering additional information and servicing a user's request have made partially observable Markov decision process (POMDP) planners particularly useful in dialog management; applications include a Nursebot robot, designed to interact with the elderly in nursing homes [71.159], a vision-based system that aids Alzheimer's patients with basic tasks such as hand-washing [71.160], an automated tele-

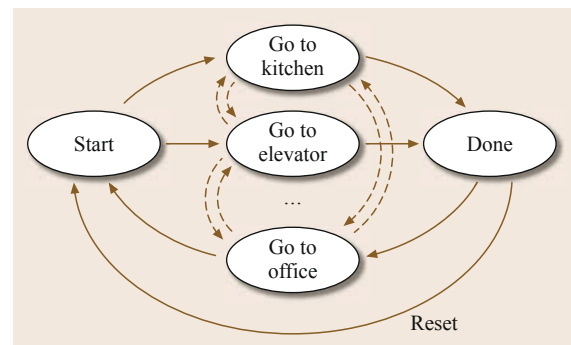


Fig. 71.19 A toy example of a dialog POMDP. The nodes in the graph are different states of the dialog (i. e., user requests). Solid lines indicate likely transitions; we assume that the user is unlikely to change their request before their original request is fulfilled. The system automatically resets once we reach the end state

phone operator [71.161], and a tourist information kiosk [71.162].

Beyond the initial formulations of cognitive HRI as a decision-theoretic problem, there have been a number of algorithmic improvements that increase the domains of applicability of this approach. For example, the conventional MDP and POMDP algorithms have typically assumed that each observation and action takes approximately the same amount of time, which can lead to an implicit bias toward longer actions. Representing time explicitly leads to computational intractability, but Broz et al. [71.163] demonstrated that the similar states that vary only by the time-index can be aggregated, leading to reduced-order models that can be solved very efficiently. Similarly, Doshi and Roy [71.164] showed that symmetries in human intentional states could be exploited to dramatically reduce the size of the planning problem, also leading to very efficient solutions. Most recently, again in the non-Bayesian line, Wilcox et al. have shown that the temporal dynamics of task-based HRI can be formulated as a scheduling problem [71.165].

Model Learning

The behavior of the dialog manager derived from solving (71.2) depends critically on accurate choices of the transition probabilities, observation probabilities, and the reward. For example, the observation parameters affect how the system associates particular keywords with particular requests. Similarly, the reward function affects how aggressive the dialog manager will be in assuming that it understands a user's request, given limited and noisy information. An incorrect specification of the dialog model may lead to behavior that is either overly optimistic or conservative, depending on how accurately the model captures the user's expectations on the interaction.

A common approach in other domains is to collect data using a fixed policy, typically referred to as system identification. In HRI, this is easiest to perform using so-called *Wizard of Oz* studies where a human experimenter executes the policy unseen to generate data or evaluate a policy. Prommer et al. [71.166] showed that Wizard-of-Oz studies could be used effectively not only to learn model parameters for an MDP dialog model, but also to learn an effective policy.

At the same time, learning all the parameters required to specify a rich dialog model can require a prohibitively large amount of data. While the model parameters may be difficult to specify exactly, either by hand or from data, we can often provide the dialog manager with an initial estimate of the model parameters that will generate a reasonable policy that can be executed while the model is improved. For example, even

though we may not be able to attach an exact numerical value to driving a wheelchair user to the wrong location, we can at least specify that this behavior is undesirable. Similarly, we can specify that the exact numerical value is initially uncertain. As data about model parameters accumulate, the parameter estimates should converge to the correct underlying model with a corresponding reduction in uncertainty.

Figure 71.20a depicts the conventional model, where the arrows in the graph show which parts of the model affect each other from time t to $t + 1$. Although the variables below the *hidden* line in Fig. 71.20a are not directly observed by the dialog manager, the parameters defining the model (i.e., the parameters in the function giving the next state) are fixed and known

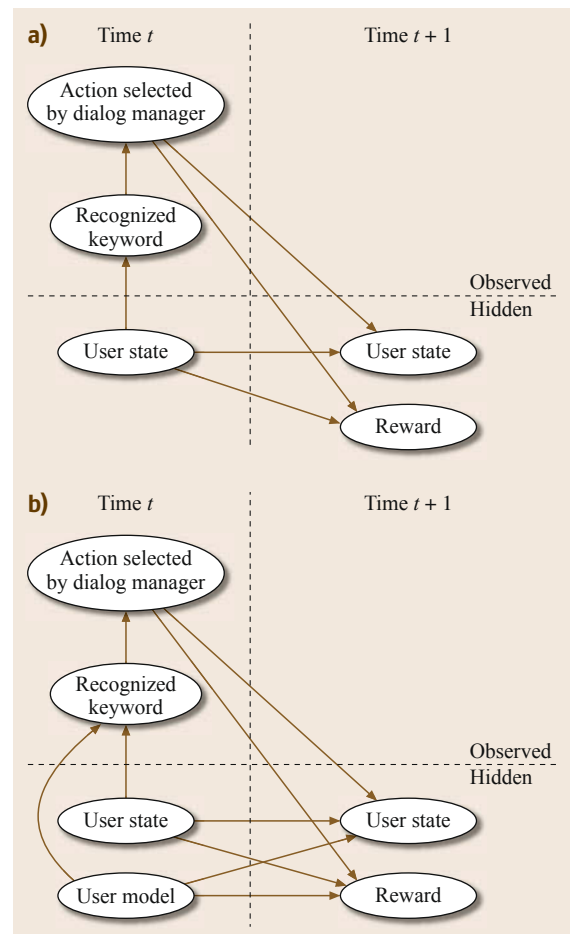


Fig. 71.20 (a) The standard POMDP model. (b) The extended POMDP model. In both cases, the arrows show which parts of the model are affected by each other from time t to $t + 1$. Not drawn are the dependencies from time $t + 1$ onward, such as the user state and user model's effect on the recognized keyword at time $t + 1$

a priori. For instance, the reward at time t is a function of the state at the previous time and the action chosen by the dialog manager.

If the model parameters are not known a priori because the model is uncertain – for example, how much reward is received by the agent given the previous state and the action selected – then the concept of the belief can be extended to also include the agent's uncertainty over possible models. In this new representation, which we call the *model-uncertainty POMDP*, both the user's request and the model parameters are hidden. Figure 71.20b shows this extended model, in which the reward at time t is still a function of the state at the previous time and the action chosen by the dialog manager, but the parameters are not known a priori and are therefore hidden model variables that must be estimated along with the user state. The system designer can encode their knowledge of the system in the dialog manager's initial belief over what dialog models it believes are likely – a Bayesian prior over models – and let the agent improve upon this belief with experience.

Poupart et al. treated the unknown MDP parameters as hidden state in a larger POMDP and derived an analytic solution (based on [71.167]) for a policy that will trade optimally between learning the MDP and maximizing reward. Unfortunately, these techniques did not extend tractably to the model-uncertainty POMDP, which is continuous in both the POMDP parameters (like the MDP) and the belief state (unlike the MDP). Doshi and Roy [71.168, 169] provided an approximate, Bayes risk action selection criterion that allows the dialog manager to function in this complex space of dialog models. This approach was applied to the intelligent wheelchair assistant shown in Fig. 71.21. Their goal was to design an adaptable HRI system, or dialog manager, that allows both the user of the wheelchair and a caregiver to give natural instructions to the wheelchair, as well as ask the wheelchair computer for general information that may be relevant to the user's daily life.

In contrast to the Bayesian approach, Cakmak and Thomaz [71.170] pursued an active learning approach and identified three types of queries that a robot could generate while learning a new task (VIDEO 237). While this result does not provide a comparison to an approach embedded in an ongoing dialogue, their results do provide guidelines for model designers.

71.3.5 Cognitive Models of Robot Control

A final line of research in cognitive HRI seeks to achieve greater task efficiency in human–robot teams, thus addressing common problems between opera-

tors and robots such as those identified by Burke et al. [71.133] and Stubbs et al. [71.134], by developing models and control interfaces that exploit mechanisms of human cognition such as working memory and mental models [71.171, 172]. This research includes formalisms such as *neglect time*, the amount of time that an operator can neglect a robot before the robot's performance drops below a certain threshold [71.171], and *fan out*, a measure of how many robots an operator can effectively manage in a human–robot team [71.172]. Such formalisms inform the development of guidelines for designing effective control mechanisms such as the following principles proposed by Goodrich and Olsen [71.171]:

1. *Implicitly switch interfaces and autonomy modes.* Context determines the mode of use. For instance, the user starts using a joystick and the interaction modality automatically switches, rather than the user explicitly selecting a modality.
2. *Let the robot use natural human cues.* The robot uses the cues to provide feedback and present information that the human uses to provide the commands or present information to the robot.
3. *Manipulate the world instead of the robot.* Control interfaces integrate knowledge about the task and the world to minimize low-level control of the robot and maintaining of a mental model of the robot's functioning.
4. *Manipulate the relationship between the robot and world.* Control interfaces provide real-world



Fig. 71.21 Our dialog manager allows for more natural human communication with a robotic wheelchair (after [71.168, 169])

representations for control to minimize low-level control.

5. *Let people manipulate presented information.* Interfaces present information in a way that represents the real world and allows users to provide input directly into the representation rather than translating information readings to a different modality or representation.
6. *Externalize memory.* Different types of information are integrated into a single representation to reduce the working memory load for the user.
7. *Help people manage attention.* The robot provides appropriate indicators to capture the attention of the operator.
8. *Learn.* Control mechanisms adapt system activity to the user's mental models.

71.4 Conclusion and Further Reading

This chapter presented an overview of research in cognitive human–robot interaction, the area of research concerned with modeling human, robot, or joint human–robot cognitive processes in the context of HRI. This research seeks to gain a better understanding of people's interaction with robots and build robotic systems with the necessary cognitive mechanisms to communicate and collaborate with their human counterparts. Three key themes fall within this research area. The first theme seeks to build a better understanding of human cognition in HRI; specifically, people's mental models of robots as ontological entities, social cognition of robot behaviors, and the use of robots as experimental platforms to study cognitive development in humans. The second theme includes research that seeks to build models for simulating human cognition in robots, gaining cognitive capabilities through imitation and interaction with the physical environment, and mapping aspects of interaction, such as commands from or references by human counterparts to objects in the environment. The final theme seeks to build models that support human–robot joint activity, including dialog-, simulation-theoretic-, joint-intention-, activity- and action-planning-based models that enable robots to reason about the physical and cognitive properties of the environment and the actions of their human counterparts and to plan actions toward achieving communicative or collaborative goals. The common thread among these three themes of research is the consideration of humans and robots as part of a cognitive

system in which cognitive processes – natural or designed – shape how humans and robots communicate and collaborate.

As an interdisciplinary area of research, cognitive human-robot interaction receives contributions from a diverse set of research fields including robotics, cognitive science, social psychology, communication studies, and science and technology studies. Further reading on the topic is also available in a diverse set of venues such as:

- *The Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction (HRI)*
- *The Proceedings of the Annual Meeting of the Cognitive Science Society (CogSci)*
- *International Conference on Epigenetic Robotics (EpiRob)*
- *The Proceedings of the AAAI Conference on Artificial Intelligence*
- *The Proceedings of the IEEE International Symposium on Robots and Human Interactive Communication (RO-MAN)*
- *The Proceedings of the Robotics: Science and Systems (RSS) Conference*
- Sun, [71.173]
- *Journal of Human–Robot Interaction*
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Video-References

- 📺 VIDEO 128 Gaze and gesture cues for robots
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- 📺 VIDEO 129 Robotic secrets revealed, Episode 1
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- 📺 VIDEO 130 Robotic secrets revealed, Episode 2: The trouble begins
available from <http://handbookofrobotics.org/view-chapter/71/videodetails/130>
- 📺 VIDEO 236 Human-robot jazz improvisation
available from <http://handbookofrobotics.org/view-chapter/71/videodetails/236>

-  VIDEO 237 Designing robot learners that ask good questions
available from <http://handbookofrobotics.org/view-chapter/71/videodetails/237>
-  VIDEO 238 Active keyframe-based learning from demonstration
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Multimedia Contents



72. Social Robotics

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This chapter surveys some of the principal research trends in Social Robotics and its application to human–robot interaction (HRI). Social (or Socialable) robots are designed to interact with people in a natural, interpersonal manner – often to achieve positive outcomes in diverse applications such as education, health, quality of life, entertainment, communication, and tasks requiring collaborative teamwork. The long-term goal of creating social robots that are competent and capable partners for people is quite a challenging task. They will need to be able to communicate naturally with people using both verbal and nonverbal signals. They will need to engage us not only on a cognitive level, but on an emotional level as well in order to provide effective social and task-related support to people. They will need a wide range of social-cognitive skills and a theory of other minds to understand human behavior, and to be intuitively understood by people. A deep understanding of human intelligence and behavior across multiple dimensions (i. e., cognitive, affective, physical, social, etc.) is necessary in order to design robots that can successfully play a beneficial role in the daily lives of people. This requires a multidisciplinary approach where the design of social robot technologies and methodologies are informed by robotics, artificial intelligence, psychology, neuroscience, human factors, design, anthropology, and more.

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72.1 Overview

The way a person interacts with a social robot (or sociable robot) is quite different from interacting with the majority of autonomous mobile robots today. Modern autonomous robots are generally viewed as tools that human specialists use to perform hazardous tasks in remote environments (i. e., sweeping minefields, inspecting oil wells, mapping mines, etc.). In dramatic contrast, social (or sociable) robots are designed to engage people in an interpersonal manner, often as partners, in order to achieve positive outcomes in domains such as education, therapy, or health, or task-related goals in areas such as coordinated teamwork for manufacturing, search and rescue, domestic chores, and more.

The development of socially intelligent and socially skillful robots drives research to develop autonomous or semiautonomous robots that are natural and intuitive for the general public to interact with, communicate with, work with as partners, and teach new capabilities. *Dautenhahn*’s work is among the earliest in thinking about robots with interpersonal social intelligence where relationships between specific individuals are important [72.1, 2]. These early works pose the question:

What are the common social mechanisms of communication and understanding that can produce efficient, enjoyable, natural and meaningful interactions between humans and robots?

Promisingly, there have been initial and ongoing strides in all of these areas ([72.3–11], etc.). In addition, this domain motivates new questions for robotics researchers, such as how to design for a successful long-term relationship where the robot remains appealing and provides consistent benefit to people over weeks, months, and even years. The benefit that social robots provide people extends far beyond strict task-performing utility to include educational (Chap. 79), health and therapeutic (Chap. 64), domestic (Chap. 65), social and emotional goals (e.g., entertainment, companionship, communication, etc.), and more.

We begin this chapter with a brief overview of a wide assortment of embodiments of socially interactive robots that have been developed around the world (Sect. 72.2). We follow with selected topics that highlight some of the representative research themes: social-emotional intelligence and emotion-based interaction (Sect. 72.3), and social-cognitive skills (Sect. 72.4). Human social responses to robots(Sect. 72.5), verbal and non-verbal communication (Sect. 72.6), long-term interaction (Sect. 72.7), touch-based interaction (Sect. 72.8), and teamwork with robot partners (Sect. 72.9). We rely on examples from our own research programs to illustrate these trends, while making reference to other excellent works performed in other research labs.

72.2 Social Robot Embodiment

72.2.1 Anthropomorphic Design

Social robots are designed to interact with people in human-centric terms and to operate in human environments alongside people. Many social robots are humanoid or animal-like in form, although this does not have to be the case. A unifying characteristic is that that social robots engage people in an interpersonal manner, communicating and coordinating their behavior with humans through verbal, nonverbal, or affective modalities. People have a strong tendency to anthropomorphize social robots [72.12] and to reason

about their behavior in terms of having their own mental states (e.g., thoughts, intents, beliefs, desires, etc.). Hence, anthropomorphic design principles, spanning from the physical appearance of robots, to how they move and behave, and how they interact with people, are often employed to facilitate interaction and acceptance.

72.2.2 Design Space

The design space of social robotics is quite large. It is important to note that a more human-like design

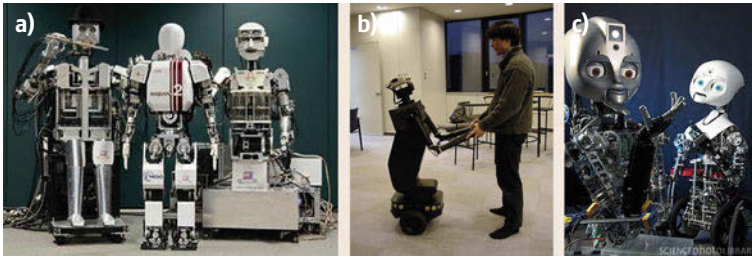


Fig.72.1a–c Examples of socially interactive humanoid robots: **(a)** Humanoid robots developed at Waseda University from left to right: a flutist robot WF-4RII (after [72.13]), WABIAN-2 (after [72.14]), and WE-4RII (after [72.15]); **(b)** Robovie developed at ATR (Advanced Telecommunications Research Institute, Kyoto) is able to gesture with its arms and give a hug; **(c)** Nexi and Maddox, developed at MIT, are mobile and dexterous social robots used to study collaborative human–robot teamwork (after [72.16])

does not necessarily correlate with a *better* design. One needs to balance the robot design with the task, user, and context [72.17]. As can be seen in the following examples, social robots exploit many different modalities to communicate and express social-emotional behavior. These include whole-body motion, proxemics (i. e., interpersonal distance), gestures, facial expressions, gaze behavior, head orientation, linguistic or emotive vocalization, touch-based communication, and an assortment of display technologies.

For social robots to close the communication loop and coordinate their behavior with people, they must also be able to perceive, interpret, and respond appropriately to verbal and nonverbal cues from humans.  **VIDEO 219** shows dog-inspired robot behaviour to facilitate intention reading by people. Given the richness of human behavior and the complexity of human environments, many social robots are among the most sophisticated, articulate, behaviorally rich, and intelligent robots today.

As shown in Fig. 72.1, a number of socially interactive humanoid robots have been developed (Chap. 65) that can participate in whole body social interaction

with people such as dancing [72.22], walking hand-in-hand [72.23, 24], playing a musical duet [72.13], or transferring skills to unskilled persons [72.25], or collaborating as a team with people in search and retrieve tasks [72.16]. Their arms and hands are designed to exhibit human-like gestures such as pointing, shrugging shoulders, shaking hands, or giving a hug [72.26–28]. Some of them are designed with mechanical faces to communicate with humans via facial expressions [72.18, 20, 29].

Whereas many of these humanoids have a mechanical appearance, android robots are designed to have a very human-like appearance with skin, teeth, hair, and clothes (Fig. 72.2). A design challenge of android robots is to avoid the *uncanny valley* where the appearance and movement of the robot resemble more of an animate corpse than a living human. Designs that fall within the *uncanny valley* elicit a strong negative reaction from people [72.37]. In contrast to trying to look as human-like as possible, there are also more doll-like robots that are intentionally designed to have simplified facial cues and predictable movements to be suitable for therapeutic contexts [72.21].

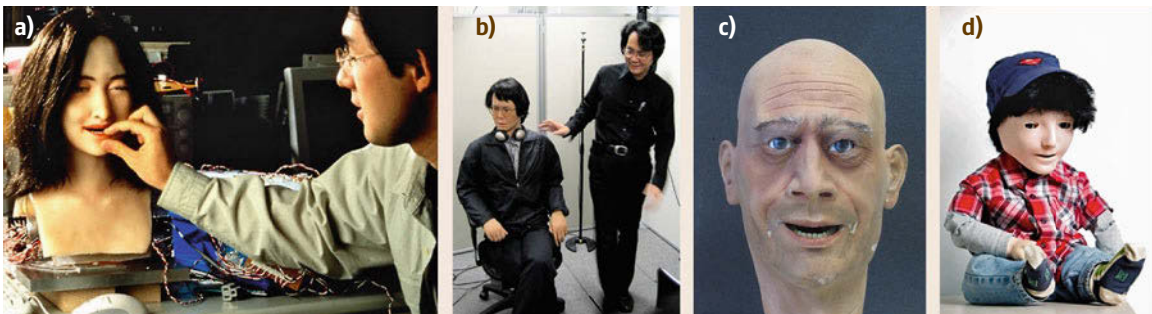


Fig.72.2a–d Some examples of androids: **(a)** One of the earliest face robots developed at the Science University of Tokyo (after [72.18]); **(b)** Geminoid developed at ATR (after [72.19]); **(c)** ROMAN developed at the University of Kaiserslautern (after [72.20]); **(d)** KASPAR developed at the University of Hertfordshire is a child like robot used during therapeutic interventions to help children with autism (after [72.21])

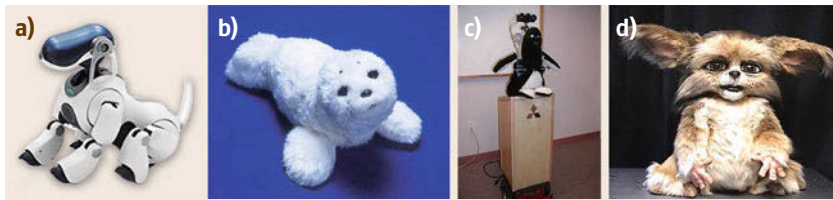


Fig.72.3a–d Examples of social robots inspired by animals with anthropomorphic qualities: (a) AIBO, the robotic dog developed by Sony (after [72.30]), (b) Paro, the therapeutic seal robot developed at AIST (after [72.31]), (c) Mel, the conversational robotic penguin developed at MERL (after [72.32]), and (d) Leonardo developed at the MIT Media Lab (after [72.33])

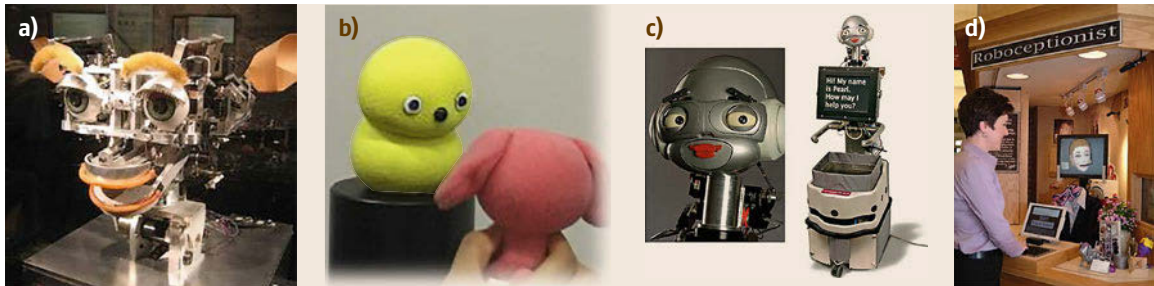


Fig.72.4a–d Examples of social robots that are neither humanoid nor zoomorphic but capture key social attributes: (a) Kismet (after [72.3]); (b) Keepon (after [72.34]); (c) Pearl (after [72.35]); (d) Valerie (after [72.36])

There are a number of more creature-like social robots that take their aesthetic and behavioral inspiration from animals (Fig. 72.3). Given that people pet and stroke companion animals, touch-based communication has been explored in several of these more animal-inspired robots. Sony's entertainment robot dog, AIBO [72.30, 38], is a well-known commercial example. Other robots in this category have a more organic appearance, such as the therapeutic companion robot seal, Paro [72.31]. Researchers have chosen to design robots with a more fanciful appearance, melding anthropomorphic with animal-like qualities such as Leonardo ([72.32, 33, 39], etc.).

Many social robots are not overtly humanoid or zoomorphic, but still capture key social attributes (Fig. 72.4). For instance, one of the best-known and pioneering social robots Kismet [72.3] developed at the MIT Artificial Intelligence Lab. Kismet had a very expressive mechanical face with anthropomorphic fea-

tures like large blue eyes. Another example is the dancing robot Keepon developed by NiCT (Japan). This small yellow robot has a simplistic face and uses a classic animation technique called *squash and stretch* for expression of the body [72.34].

Many mobile social robots have been fitted with faces to enhance social interaction (Fig. 72.4). Some examples are the eldercare robot, Pearl [72.35], and the robotic receptionist Valerie with a graphical face on a LCD (liquid crystal display) screen [72.36], both developed at Carnegie Mellon University. Other examples are commercial robots like PaPeRo developed by NEC [72.40]. Still, some social robots have no overt social features like faces or eyes, but rely purely on language-based communication. Issues of proxemics on mobile social robots have also been explored such as how a robot should approach a person [72.41], follow a person [72.42], or maintain appropriate interpersonal distance [72.43].

72.3 Social Robots and Social-Emotional Intelligence

Humans are fundamentally emotional beings. Consequently, human communication and social interaction often includes affective or emotive factors. To support the emotional side of human behavior, researchers are exploring affective interaction and communication

between people and robots. To participate in emotion-based interaction, robots must be able to recognize and interpret affective signals from humans, they must possess their own internal models of emotions (often inspired by psychological theories), and they must be able

to communicate this affective state to others. In general, emotional displays can inform the interpretations about an individual's internal states (agreement or disagreement about a belief, valuing a particular outcome, an action tendency to fight, etc.) and therefore help to predict future actions. Emotional displays can evoke emotional responses in others (e.g., displays of distress can elicit feelings if empathy and motivate another to provide social support). Given that social interactions can serve such a broad range of functions, prominent scientists have argued that emotions evolved because they provide an adaptive advantage to social species where individual relationships matter [72.44].

A growing number of socio-emotional robots have been designed to realize such functions to facilitate human-robot interaction. Some of these robots have been designed with emotional responses or emotion-inspired decision making systems in order to entertain AIBO [72.30], QRIO [72.45, 46], conversationally engage with WE-II [72.47], or bond with people [72.48, 49]. Some have investigated the social-communicative aspects of emotions in coordinating behavior and influencing others, e.g., FEELIX [72.50], Kismet [72.3, 51]. Others have explored the functional role of emotion-inspired processing in order to make robots more intelligent, better able to learn, and better adapted to performing tasks in complex environments [72.52]. More recently, researchers have investigated the role of affect in the context of robots that work with people and perform tasks such as search and rescue/retrieve [72.16, 53, 54]. Finally, others model emotions to make robots better able to handle human emotional states, and to motivate people toward more effective interactions in a range of application domains such as education [72.55], coaching [72.56], or therapeutic systems [72.31].

72.3.1 Theories of Emotion

The robot's computational model of emotion determines the robot's affective responses. This can depend on a myriad of interrelated physical, cognitive, and affective factors that continuously modulate and bias one another. These factors arise from the robot's interactions with the external environment as well as its own internal state (i.e., the current emotional state, the cognitive state, goals, motives, physical states, etc.). The emotional model defines the relationship between these factors and mechanisms that result in the observable behavior of the robot. Many of these computational models of emotion are inspired by theories of human emotions. These theoretical models offer insightful constraints that help researchers to derive coherent computational models.

A number of theoretical perspectives have been particularly influential in the development of computational models of emotion. Appraisal theory emphasizes a causal connection between cognition and emotion [72.57]. In appraisal theory, emotion is evoked from patterns of judgments (called appraisal variables) that characterize the personal significance of events (e.g., events and the individual's beliefs, or desires and intentions). An active area of development is in understanding the relationship between appraisal variables and specific emotion labels, or specific behavioral (i.e., facial expressions) and cognitive responses (i.e., coping strategies) [72.58]. This kind of model lends itself to more symbolic AI (artificial intelligence) implementations, with if-then rules [72.59, 60]. In contrast, dimensional theories posit that emotion and other affective phenomena are not discrete entities, but rather exist on a continuum of a continuous dimensional space [72.61]. Smith and Scott [72.62] proposed a three-dimensional (3-D) PAD model where P corresponds to pleasure (valence), A corresponds to arousal (intensity), and D corresponds to dominance (coping potential) [72.62]. Reference [72.63] mapped these appraisal dimensions to intensity varying expressions that can be computed as a weighted blend of basis postures corresponding to the main axes [72.63]. The core affect (the emotional state of the individual at any given time) is represented as a point in the 3-D space that is pushed around by eliciting events. Dimensional models are often used for generating the behavior of animated characters, as the dimensional space lends itself nicely to animation blending.

72.3.2 Example: A Synthesis of Emotion Theories in Action

Kismet is the first autonomous robot explicitly designed to explore socio-emotive face-to-face interactions with people [72.3, 51]. Research with Kismet focused on exploring the origins of social interaction and communication in people, namely that which occurs between caregiver and infant, though extensive computational modeling guided by insights from models of emotion [72.64]. Kismet was designed to be dependent on people to help it satisfy its goals and motivations.

Internally, Kismet's models of emotion interacted intimately with its cognitive systems to make affective appraisals about its interactions with the surrounding environment and people. These appraisals characterized the robot's interaction with its environment (e.g., *Is an object too close to the robot so that it might do damage?*, *Is that person speaking to me in a praising tone of voice?* etc.). These appraisals were tagged

with somatic markers [72.65] that characterized how these appraisals mapped to the robot's internal measures of arousal (A), valence (V), and stance (S), an action tendency to approach or avoid). The affective appraisals directly influenced the robot's behavior selection and goal arbitration processes. The somatic markers influenced the robot's core affective state – a continuously adjusted point within a three dimensional $[A,V,S]$ space. The core affect mapped to the robot's emotive expressions conveyed through vocal quality, facial expressions, and body posture [72.66]. Rather than simply triggering a set of discrete emotive expressions, Kismet's facial and postural expressions were continuously computed following a componential approach, as a weighted blend of basis postures of the face and body along the $[A,V,S]$ axes. This subtle variability in expressive behavior was important for enabling the robot to mutually regulate affective states with a person [72.67, 68]. Finally, the core affect and affective appraisals contributed to elicit adaptive behavioral responses (e.g., orient, search, avoid, etc.) as part of the robot's emotive responses (loosely inspired by the idea of emotion circuits [72.69]). Through a process of behavioral homeostasis [72.70], these emotive responses served to influence how people interacted with the robot in order to restore the robot's internal drives, goals, and affective states [72.67, 68].  VIDEO 557 illustrates Kismet's ability to recognize, express and interact with people using emotive cues. Ultimately, the purpose of this *dance* was to keep the robot in a *zone of proximal development* conceptualized by Vygotsky to be optimal for learning to propel the robot down a developmental path [72.71].

72.3.3 Emotional Empathy

For humans, the dynamic coupling of like minds through the actions of similar bodies is critical for acquiring human-like intuitions about the internal states of others. Dautenhahn [72.2] is one of the earliest works to explore *empathic* mechanisms of understanding others in social robot–robot interaction.

It is likely that emotional empathy in humans is learned, beginning in infancy. Various experiments with human adults have shown a dual affect–body connection whereby posing one's face into a specific emotive facial expression actually *elicits* the feeling associated with that emotion [72.72, 73]. Hence, imitating the fa-

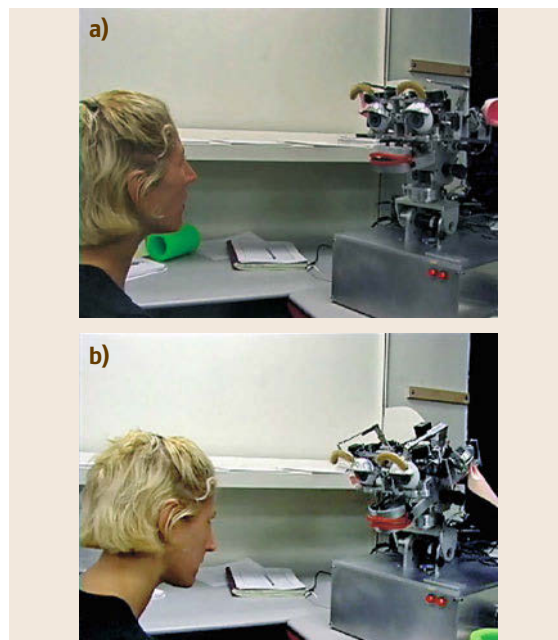


Fig.72.5a,b Kismet and a young woman mirroring affect. Facial expression and affective tone of voice are tightly correlated: **(a)** mirroring interest/arousal; **(b)** mirroring negative affect

cial expressions of others could cause an infant to feel what the other is feeling, thereby allowing the infant to learn the association of observed emotive expressions of others with the infant's own internal affective states. Other time-locked multimodal cues may facilitate learning this mapping, such as affective speech that accompanies emotive facial expressions during social encounters between caregivers and infants. Using a similar approach, Breazeal et al. [72.74] posit that a robot could learn the affective meaning of emotive expressions signaled through another person's facial expressions, body language, and synchronized multimodal cues such as vocal prosody [72.68, 75] (Fig. 72.5). These time-locked multimodal states occur because of the similarity in bodies and body-affect mappings, and they enable the robot to learn to associate its internal affective state with the corresponding observed expression. In later work, they implemented a model of social referencing by which the robot, Leonardo, that combines models of *empathic association* with models of shared attention (Sect. 72.4.1).

72.4 Socio-Cognitive Skills

Socially intelligent robots, however, must understand and interact with animate entities (i. e., people, animals, and other social robots) whose behavior is governed by having a mind and body. In other words, social robots need the ability to recognize, understand, and predict human behavior in terms of the underlying mental states such as beliefs, intents, desires, feelings, etc. Psychology calls this ability *Theory of Mind* (also known as mindreading, mental perception, social common-sense, folk psychology, social understanding, among others).

This section reviews research in implementing models of human socio-cognitive skills and abilities on robots. Social robots shall need a diverse repertoire of such skills to realize their full potential in daily human life – to communicate, cooperate, and learn from people in a human-centric and human compatible manner.

For instance, social robots will need to be aware of people's goals and intentions so that they can appropriately adjust their behavior to help us as our goals and needs change. They will need to be able to flexibly draw their attention to what we currently find of interest so that their behavior can be coordinated and information can be focused about the same thing. They need to realize that perceiving a given situation from different perspectives impacts what we know and believe to be true about it. This will enable them to bring important information to our attention that is not easily accessible to us when we need it. Social robots will need to be deeply aware of our emotions, feelings, and attitudes to be able to prioritize what is the most important thing to do for us according to what pleases us or to what we find to be most urgent, relevant, or significant.

Furthermore, the behavior of social robots will need to adhere to people's expectations. Namely, people will apply their theory of mind to understand the robot in terms of these mental states as well.

72.4.1 Shared Attention

Scassellati [72.76] was one of the earliest works to pose the question of how to endow robots with a theory of other minds. Inspired by the theoretical viewpoints proposed from the study of autism (believed to be a deficit of theory of mind), Scassellati implemented a hybrid model of those models proposed by Leslie [72.77] and Baron-Cohen [72.78] where shared attention is viewed to be a critical (and missing) precursor to the theory of mind competence. This hybrid model was implemented on the humanoid robot, Cog. The robot was able to exhibit an assortment of social-cognitive skills such as joint attention, distinguishing an entity in the

environment as either being animate or inanimate, and imitating only entities deemed to be animate [72.79].

Several researchers have explored models of joint reference, guided by insights provided by developmental psychology and autism research [72.76, 79–81]. Normal human infants first demonstrate the ability to share attention with others at 9 to 12 months of age, such as following the adult's gaze or pointing gestures to the object being referred [72.78, 82]. In these works, joint attention is a learned process. For instance, the robot learns the visual motor mapping from the human's attentional cue (often using head pose as a popular indicator of what the human is currently looking at) to the motor commands necessary to have the robot look at the same thing. This process is often bootstrapped by having the human look to where the robot initiates its gaze. In Fasel et al. [72.80], the robot learns a model of joint attention because it discovers that the human's gaze is a reliable indicator of where there is something interesting to look.

Thomaz et al. [72.83] explore attention-monitoring behavior of a robot in a social referencing interaction. In the developmental psychology literature, the ability for babies to actively monitor that others are looking at the same thing is a strong indicator of shared attention [72.84]. Social referencing is considered to be an early demonstration of shared attention because the baby looks back and forth between the novel object and the adult's emotive reaction toward that object to learn the association between the two. To implement shared attention, the robot's attentional state is modeled with two related but distinct foci: the current attentional focus (what is being looked at right now) and the referential focus (the current topic of shared focus, i. e., what communication, activities, etc. are *about*). Furthermore, the robot maintains a model for its own attentional state and a model for the attentional state of the human. The robot uses the heuristic of looking time upon a shared object to infer the referent of the interaction. Once the referent has been identified, the robot monitors the attention of the human in order to associate their emotional reaction about that object to the intended target. Video  VIDEO 556 illustrates Leonardo's ability to interact and learn from a person via social referencing.

72.4.2 Mental Perspective Taking

This section explores this empathetic, self-as-simulator approach further to address more general challenges in endowing robots with mental perspective-taking abilities. These approaches are inspired and informed by

theories championed by neuroscience and embodied cognition called *Simulation Theory*.

Simulation Theory

Simulation theory holds that certain parts of the brain have dual use; they are used to not only generate our own behavior and mental states, but also simulate the introceptive states of the other person [72.85]. In other words, we engage in a process of perspective taking and mental simulation.

For instance, *Gallese and Goldman* [72.86] proposed that a class of neurons discovered in monkeys (called *mirror neurons*) is a possible neurological mechanism underlying both imitative abilities and Simulation Theory-type prediction of the behavior of others and their mental states. Further, *Meltzoff and Decety* [72.87] posit that imitation is the critical link in the story that connects the function of mirror neurons to the development of adult mind-reading skills. From the field of embodied cognition, *Barsalou et al.* [72.88] presents additional evidence from various social embodiment phenomena that when observing an action, people activate some part of their own representation of that action as well as other cognitive states that relate to that action.

Mirror Systems for Recognizing Actions

Inspired by these theories and findings, *Johnson and Demiris* [72.89] employ a simulation of visual perception to recreate the visual egocentric sensory space and corresponding egocentric behavioral space of the observed agent to increase the accuracy of action recognition. This approach is based on their *HAMMER* architecture (hierarchical attentive multiple models for execution and recognition) that takes a mirror neuron inspired approach to action recognition and imitation by directly involving the observer's motor system in the action recognition process. Specifically, during observation of another's actions, all of the observer's inverse models (akin to motor programs) are executed in parallel via simulation using forward models, and then compared to the observed action. The one that matches best is selected as being the recognized action. Perceptual perspective taking is needed to provide meaningful data for comparison. The simulated actions used by the observer during recognition must be generated as though from the point of view of the other person. They demonstrate this approach in an experiment where a robot attributes perceptions and recognizes the actions of a second robot [72.89].

Mental Perspective-Taking for Inferring Beliefs and Goals

Gray et al. [72.90] have implemented computational models of simulation-theoretic mechanisms throughout

several systems within Leonardo's cognitive architecture to enable the robot to infer beliefs and goal states of a human collaborator.

The robot reuses its belief-construction systems from the visual perspective of the human to predict the beliefs the human is likely to hold to be true given what he or she can visually observe. This enables the robot to recognize and reason about the beliefs held by a person, even when they diverge from the robot's own beliefs of the same situation.

In psychology, the ability to appreciate the divergent beliefs of another is classically demonstrated by the famous false belief task. In this task, subjects are told a story with pictorial aides that typically proceeds as follows: two children, Sally and Anne, are playing together in a room. Sally places a toy in one of two containers. Sally then leaves the room, and while she is gone, tricky Anne moves the toy into the other container. Sally returns. At this point the human subject is asked *Where will Sally look for the toy?*

The robot, Leonardo, has demonstrated its ability to pass these sorts of false belief tasks where it observes two humans playing the roles of Sally and Anne [72.91]. Within the robot's goal-directed behavior system (where schemas relate preconditions and actions with desired outcomes) motor information is used along with perceptual and other contextual clues (such as hierarchically structured task knowledge) to infer the human's goals and how he or she might be trying to achieve them (i. e., plan recognition).

72.4.3 Perspective Taking in Collaboration and Teamwork

By using a simulation-theoretic methodology, mental inferences made across different cognitive systems can interact in interesting and useful ways to support collaborative behavior where a robot offers its human teammate appropriate assistance.

Using Visual Perspective Taking to Resolve Ambiguous Referents

Trafton et al. [72.92] have developed and implemented visual and spatial perspective taking abilities based on mental simulation to support human-robot interaction and collaboration. Their cognitive architecture, *Polyscheme*, is designed to model how humans integrate multiple representational methods, reasoning, and planning methods to keep track of the world, including rich facilities for representing counterfactual worlds. It thus supports simulations of other people's visual perspective to reason about interactions and the world from this alternate point of view.

They have demonstrated these skills in a number of experiments, such as demonstrating the robot's ability to learn how to play *hide and seek* with a person where the robot learns what makes a good hiding place with respect to being completely occluded from the human seeker's point of view [72.93]. They have also demonstrated the usefulness of this system for a robot that solves a series of perspective-taking problems using the same frames of references and spatial reasoning abilities that astronauts do to facilitate collaborative problem solving – such as repairing a vehicle with another person that has a different vantage point [72.94]. For instance, the robot can handle egocentric requests (i.e., *hand me the cone to my right*), addressee-centric requests (i.e., *hand me the cone to your right*), or object-centered requests (i.e., *hand me the cone in front of the box*).

In Trafton et al. [72.92], a human interacts with the robot using a multimodal interface that supports speech and gesture. The robot's perspective taking skills are used to resolve ambiguous referents that can arise when a person asks a robot perform an action in relation to an object (i.e., asking the robot to *hand me the wrench* when there are multiple wrenches to choose from). In particular, a visual occlusion in the workspace might hide another candidate wrench from the person's viewpoint but not from the robot's viewpoint (Fig. 72.6). The robot can infer which is the intended object by taking the visual perspective of the human and applying principles of *joint salience* and *least effort*. If there still remains an ambiguity, the robot can act to resolve it by asking *which one?*

Providing Informational or Instrumental Support

Gray et al. have demonstrated the ability for the Leonardo robot to successfully infer its human partner's beliefs, desires, and intentions from real-time behavior during collaborative tasks. The shared workspace can have either visual occlusions [72.90] or can change dynamically where not all participants know of these changes [72.91]. The robot can integrate these mental state inferences to decide how to best help the person such as offering instrumental support (acting on the environment to help the human complete their goal) or provide informational support (giving relevant information the person needs to successfully achieve his or her goal).

Consider the following scenario: a helpful robot is introduced to two people, Sally and Anne. All three watch as Anne hides chips in a box to the left of the robot and cookies in a box to the right. Sally leaves the room, at which point Anne plays a trick on Sally by swapping the contents of the boxes and then locks both

boxes with a combination lock. Anne leaves, and Sally soon returns craving the chips she saw placed in one of the boxes. Sally remembers seeing the chips placed in the left box and attempts to open it by working the combination lock. The robot has matching chips and cookies that it can give out. What should the robot do to assist Sally?

Mindreading skills play an important role in this plan recognition scenario where the robot must observe Sally in real time to infer Sally's misconception of where the chips are (Anne switched the location when Sally was out of the room), to infer what her desire is based on her behavior (Sally never explicitly said she wants the chips), and to recognize that Sally's plan for how to get the chips is actually invalid (she is trying to open the wrong box). The robot has true knowledge of the situation, and must then reason about how to best help Sally get the object of her desire.

Gray et al. [72.91] (VIDEO 563) combines these three kinds of mental inferences to demonstrate intention recognition with divergent beliefs for collaborative robots. Specifically, for the case of informa-



Fig. 72.6 Robonaut using visual perspective taking to disambiguate the intended referent when asked to *hand me the wrench*. The human can only see one wrench, but the robot can see both. The robot correctly hands the wrench that both can see

tional support, Leonardo relates its own beliefs about the state of the shared workspace to those of the human based on the visual perspective of each. If a visual occlusion exists or an event occurs that prevents the human from knowing important information about the workspace, the robot knows to direct the human's attention to bring that information into com-

mon ground. For instance, Leonardo points to the box that actually holds the chips. For the case of instrumental support, Leonardo helps the person by directly giving the person a matching bag of chips. Gray and Breazeal [72.95] explore the robot reasoning and taking explicit action to deceive a human competitor.

72.5 Human Social Responses to Social Robots

72.5.1 Social Judgments

Anthropomorphic design is important for social robots given that the appearance, interface, and function of a technology or product impact how people perceive it, interact with it, and engage with it over time [72.12]. Robots and other technologies with humanlike design cues elicit social responses from people [72.96–99]. For instance, people have been found to respond more positively to artifacts that exhibit humanlike cues such as emotive expressions over those with a purely functional design, although user preferences were task and context dependent [72.100, 101]. Adding humanlike cues to a technological artifact can foster people's social connection to it, aid people in learning how to use it, and enhance liking, engagement, and the desire to collaborate [72.102–104]. Others have found that people tend to hold richer mental models of as anthropomorphic robots than mechanistic ones [72.103, 105]. Others have explored a number of anthropomorphic design features such personality, backstory, use of humor, and even the notions of self (e.g., referring to itself as *I*), deception, politeness, and moral regard [72.106–108]. However, it is important that the appearance and interface of the robot's design match its capabilities and the users' expectations or negative effects can result [72.109].

72.5.2 Physical Versus Virtual Embodiment

When considering the role and advantages of social embodiment, one might ask whether there is a difference between physical and virtual counterparts. Indeed, physical social embodiment offers a number of advantages over purely graphical representations. First, while many social interactions involve exchanging only visual and auditory cues, robots support communication and collaboration through physical contact as well. Robots support the joint manipulation of artifacts and the sharing of physical space with people. Both are important for all sorts of collaborative activities such as assembly and manufacturing [72.110, 111] search and

rescue [72.16, 53], domestic assistance [72.103], and more. Further touch is not only an interesting and important communication modality with noted health and therapeutic benefits, but it can also influence the social judgments people make of robots such as how caring or persuasive it is perceived to be [72.103, 104]. The modality of touch will be discussed further in section social touch [72.31, 39].

In addition, a growing number of studies that directly compare virtual to physical agents report that people show more trust, compliance, and enjoyment with physical robots [72.112–115]. Beyond user preference of physical over virtual agents, a number of studies have also shown improved human performance and outcomes on a wide variety of tasks ranging from games [72.112] to educational contexts [72.115], assistive tasks [72.114], health-related activities [72.116], and Wizard-of-Oz user studies [72.113].

Finally, because virtual agents are a representational form, interpretation and mapping may prove too challenging for individuals with cognitive or social deficits. Hence, robots may prove advantageous as therapeutic interventions for children with autism who can show little or no interest in forms on video monitors or televisions [72.117]. Finally, social robots tend to support face-to-face group dynamics [72.118] – while screens tend to *capture eyeballs* at the risk of diminishing face-to-face interaction [72.119]. This has important considerations for the design of learning technologies for young children, in particular, where supporting the participation of the parent in a social way is of great benefit to how children learn.

72.5.3 Social Stimulus to Learn About People

The impact of physically embodied social robots on human social responses has opened new applications for robots as an interesting tool to help scientists learn about human social behavior and judgments. People make a variety of social judgments through the dynamic exchange of nonverbal cues such as postural

shifts, subtle head gestures, arm gestures, facial cues, tone of voice, etc. Indeed, ample evidence indicates that humans regularly use specific cues, often without conscious awareness, to infer the motivations of others with some level of accuracy [72.120, 121]. If people employ such cues without conscious awareness, then it becomes difficult to use people as experimental confederates where such cues must be carefully controlled. Thus, in one paradigm, social robots can be used as a highly controllable social stimulus in the place of a confederate in human participant studies. This is particularly useful when trying to understand how human nonverbal cues influence people's social judgments, such as how trustworthy another is perceived to be from a brief encounter [72.122].

72.5.4 Social Rapport

One important skill for social robots is the ability to build and maintain social rapport with its user. Social rapport exists in the interaction between individuals. It creates a powerful interpersonal influence and responsiveness based on mutual attentiveness, positivity, and mutual responsiveness [72.123–126]. In joint activities, the ability to establish a good rapport often results in improved outcomes. For instance, students learn better when they have a good rapport with their teachers [72.127], patients are more adherent and have better health outcomes when they have a good rapport with their doctors [72.124], teams make better decisions and work more effectively when they share a good rapport with each other [72.128]. The quality of rapport between people is influenced by the exchange of nonverbal behaviors between individuals [72.129, 130]. Although the specifics of how people build a strong rapport with one another are still a topic of scientific inquiry, the more in-sync and open the participants' nonverbal cues are in relation to one another, the more positive rapport results. For instance, appropriate mirroring or synchrony of body posture, head movements, facial expression, and vocal prosody can all contribute to positive rapport. Open cues signal a receptiveness to interact, e.g., making appropriate eye contact, leaning toward another, and arm gestures that tend to not occlude the body or face.

Hence, when considering how social robots can effectively collaborate with people, their ability to build and maintain good social rapport with people (at least perceived rapport) is important. Thus, it is not just a robot's ability to perform such nonverbal cues that ultimately matters, but the robot's ability to coordinate them with those of people in real-time. For instance, researchers have explored the coordination of an agent's

nonverbal cues with people to improve rapport [72.56], engagement [72.32], trustworthiness [72.122], and deictic cues [72.131].

72.5.5 Social Support

Improved rapport also facilitates the ability of social robots to provide people with effective forms of social support. Social support is recognized to play an effective role in helping people to attain personal goals and improved outcomes in broad domains such as education, mental health, physical health, aging, coping, and more. It is conceptualized as the perception and actuality that one is cared for, has assistance available from others, and that one is part of a supportive social network [72.123]. These supportive sources can be emotional, instrumental, informational, or companionship. Emotional support, for instance, conveys to an individual know that they he or she is valued; it includes offering empathy, concern, nurturance, encouragement, and acceptance to name a few [72.124, 125]. Instrumental support concerns the concrete, utilitarian ways to provide assistance such as financial assistance, material goods, or services. Informational support includes offering useful advice, guidance, or information to help others problem-solve. Finally, companionship support gives someone a sense of social belonging and having another to participate in shared social activities. These forms of social support can come from people, professionals, pets, and even social robots.

The ability to provide a user with social support is one of the effective ways that social robots can help people through social means. Robots can provide this assistance through direct interaction with its user, or by helping to mediate the provision of social support from people (e.g., connecting people). A wide variety of social robots today are being developed to interact with people as tutors [72.132], learning companions [72.118, 133], coaches [72.116], domestic helpers for the elderly [72.134], therapeutic aids [72.21, 31], and more. Through dialog, nonverbal cues, expressive displays, and physical actions, these robots assist people by providing information, monitoring performance, offering feedback, incentivizing and sustaining motivation, giving encouragement, offering companionship, performing physical tasks, etc.

As such, social robots have broad applicability in many domains where it is a technology that can extend and augment the social support provided by people. This is particularly relevant for societal challenges, e.g., eldercare, health and chronic disease management, and education, where social support is recognized as being critical for positive outcomes, but where there is a rec-

ognized shortage of trained professionals to meet the demand. Further, whereas frequent meetings with human professionals is cost prohibitive, social robots have the potential to be used to *fill the gaps* in a cost-effective

way. Importantly, social robots are not being designed to replace or obviate human professionals, but rather to serve an effective tool that supports human networks in a scalable and cost-effective way.

72.6 Social Robots and Communication Skills

Communication implies an exchange of information through natural language. Thus, one might consider that very good **ASR** (automatic spoken-language recognition) is the primary function required to fulfill the communication skills for robots. However, *social* robots are expected to engage in casual communication with people in as natural a way as people communicate themselves. In such casual communication, information is often exchanged nonverbally as well as verbally. Thus, robots need to be well equipped to recognize people's nonverbal cues and to express nonverbal cues via their nonverbal behavior. The required computation even takes into account good perceptual and cognitive capability of surrounding environments in addition to the targeted person. This section introduces the history of research in social robots and communication skills, and provides insights for future challenges.

72.6.1 Verbal/Nonverbal Communication

Historically, even first-generation humanoid robots developed in the 1970s had primitive capabilities for communicating using natural language. For instance, WABOT and WABOT-2 had a conversation capability in natural language, which is based on the model as simple combinations of speech input/output mappings [72.135, 136].

Furthermore, early pioneers had noticed the importance of nonverbal information in human conversation. Nonverbal behavior was classified into three roles:

1. **Regulators:** expressions such as gaze, poses, and vocalizations that are used to regulate/control conversational turn-taking.
2. **State displays:** indication of internal state including affect, cognitive, or conversational states that improve interface transparency.
3. **Illustrators:** gestures that supplement information for the utterance. These include deictic gestures (pointing) and iconic gestures.

In this scope, nonverbal information is considered as supplemental. It is natural language that communicates the primary information in turn-based exchanges. We provide examples below.

Regulatory Cues

Even some of the earliest social robots displayed nonverbal information to regulate interactions with people. Hadaly 2 was the first robot to use mutual gaze as a nonverbal cue to regulate conversation [72.137, 138]. The mutual gaze is approximated using face recognition to determine when the human's face was facing the robot; when a mutual gaze occurred, Hadaly 2 expressed readiness to commence conversation by blinking its eyes. People's gaze toward a robot is also considered cues to inform whether he/she is engaging in the conversation with the robot [72.139].

Other examples are Kismet [72.3, 140, 141] and Leonardo [72.33, 142], which had the capability for nonverbal cues called envelope displays to regulate the exchange of speaking turns. Backchannelling cues were found to reduce stress and cognitive load during complex human-robot teaming task (Fig. 72.7). See  **VIDEO 559** for how Kismet uses envelope displays to regulate speaking turns with people. The regulatory role for a speaking turn is demonstrated in multi-party interaction too. People tend to make eye contact and raise their eyebrows when they are ready to relinquish their speaking turn and tend to break their gaze and blink when starting their speaking turn. Recognition of these cues was implemented for smoothing and syn-

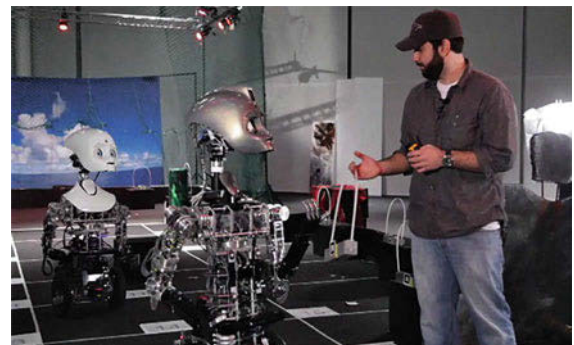


Fig. 72.7 Backchannelling cues were found to reduce stress and cognitive load during complex human-robot teaming task. Teams where the robots engaged in backchannel cues to human requests also tended to find more items in a search and retrieve task (after [72.16]),

 **VIDEO 555**

chronizing the exchange of speaking turns. Gaze is also known to convey the speaker's intention who may take the next turn. *Mutlu et al.* have successfully replicated it in human–robot interaction [72.143, 144]. *Kirchner and Alempijevic* revealed that gaze is also effective in communicating who should receive an item provided by a robot [72.145]. In opposite way, gaze was also used as a cue to interpret whether one would wish to take turn [72.146].

Paralinguistic information is also processed. People frequently provide short acknowledgment utterances (e.g., *uh-huh, um-hmm, huh*, etc.) as the robot explains something. These responses are either acknowledgments, or ask-backs. It is very difficult to distinguish these two kinds of utterances from only the linguistic information as represented by the transcription of the utterance. *Fujie et al.* demonstrated a method to distinguish the utterance as either an acknowledgment or an ask-back from the prosody of utterance [72.47].

State-Display Cues

The facial expression and gaze were used to indicate the conversational or cognitive state of a robot. Such state-display cues make the robot's internal state more transparent to a user and thus enables him/her to better understand the robot's state. For instance, *ROBITA* used the tightness of its facial expression to indicate readiness to engage in conversation; a tight face was used to express conversational readiness, while a loose face communicated a lack of readiness to engage [72.147]. Emotional state and attention target can also be displayed nonverbally (Sects. 72.3 and 72.4).

State of listening and level of understanding are also displayed nonverbally. Human listeners use back-channel responses, such as head nods to convey the fact that he/she is successfully following the conversation. Imitating human behavior, robots indicate their state of listening using head nods [72.148], facial expressions [72.5], and bodily motion ([72.149] and  VIDEO 810). Such state-display cues are used in a human-like telepresence robots to indicate operators' state of being engaging to the conversation [72.150, 151].

Another back-channel signal is an expression of confusion by the listener (verbal or nonverbal). This flags the speaker to stop and try to repair the broken communication. Robots such as *Leonardo* and *ROBITA* use facial displays of confusion when speech recognition fails in order to intuitively communicate to the human that he or she should repeat their last utterance.

There were robots that process humans' back channel feedback [72.32]. A sophisticated head nod recognition system was developed whereby the robot, *Mel*,

could successfully distinguish small feedback nods from other kinds of head nods such as those that communicate agreement. *Mel* used this information to determine its own nodding behavior in order to be an appropriate response for the human. In a series of human subject studies, *Sidner et al.* found these nonverbal cues to enhance the social engagement of the robot to people [72.32].

Illustrator Cues

Deictic gestures have often been implemented in robots for pointing to an object, such as using index-finger pointing [72.152, 153], gaze [72.143], and the combination of the two [72.74, 154–157]. Other types of gestures, such as iconic gestures [72.156] and region pointing ([72.158] and  VIDEO 811), were also successfully used in robots. The effect of gestures has been successfully demonstrated. For instance, in a direction giving scenario, even though turn-by-turn direction is verbally given thus could be comprehend without gesture, supplemental pointing gesture improved listeners' comprehension about the given direction [72.159].

A number of robots are able to recognize deictic gestures of a person conveyed either through pointing gestures or head poses. For example, *Leonardo* is able to infer the object referent in an interaction by considering a number of factors including pointing gesture, head pose, and speech. *Sugiyama et al.* associated verbal spatial deixis and pointing gestures to better recognize the pointed target ([72.160] and  VIDEO 807). *Brooks and Breazeal* [72.153] developed a deictic recognition system that enabled a robot to infer the correct object referent from correlated speech and deictic gesture. Interestingly, it was found that the accuracy of the human's pointing gesture is surprisingly poor. As a result, the deictic recognition system relies on coordinated speech and gesture information, with spatial knowledge provided by a three-dimensional (3-D) spatial database constructed by the robot using real-time vision, and a deictic spatial reasoning system. This system was successfully demonstrated on the dexterous humanoid *Robonaut* developed at National Aeronautics and Space Administration (*NASA*) Johnson Space Center (*JSC*) (Fig. 72.8b) where the human points to and labels a set of four bolts on a wheel to be fastened in order by the robot.

72.6.2 Mechanisms for Human–Robot Communication

Mechanisms of turn-based communication are well studied. In linguistics, it is considered that conversation is formed as the repetition of turn-taking [72.161].

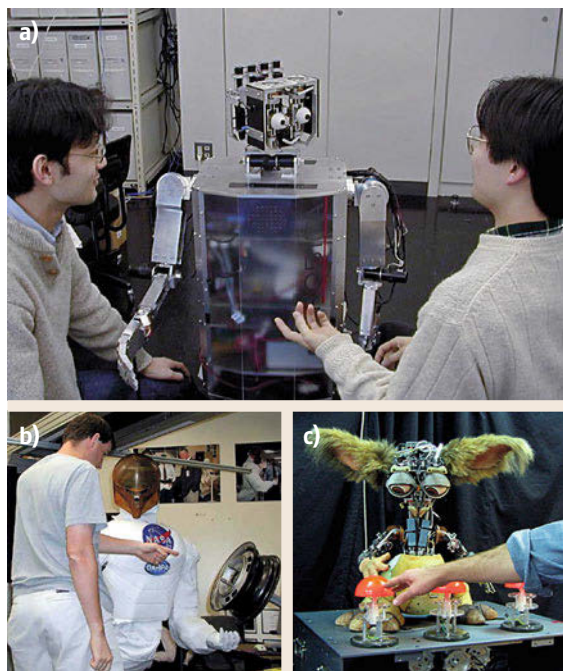


Fig.72.8a–c Examples of conversational robots: (a) ROBITA performing group conversation; (b) Robonaut interpreting the pointing gestures of a human to determine which nut to fasten on the wheel; (c) Leonardo uses gaze and joint attention to ground the human's pointing gesture for the desired referent

There is one speaker who takes floor and speaks while listeners listen to him/her [72.162]. When the speaker finishes speaking, then the floor is taken by one of the listeners. There could be bystanders who also listen to, but do not intend to take turn. This turn-based model is the typical model used in dialog modeling [72.163]. That is, a dialog management system identifies who owns floor, recognizes words in utterances the speaker spoke, and generate utterance when the system takes floor, often implemented with series of rules. It is successfully extended for human–robot communication. For instance, *Nakano* et al. developed rule-based architecture in which the planner deals with robot's task-based actions as well as dialog management [72.164]. *Scheutz* et al. developed software architecture, named DIARC. It uses a rule-based planner that receives inputs from all perception modules, and addresses effect and goal-directed actions in addition to natural language dialog management [72.165]. In such an approach, the robot communicates through utterances accompanied with nonverbal cues [72.166]. Some systems deal with multi-party dialog, in which robot's gaze-cue (Fig. 72.8a) is used to regulate who is the addressee, the active listener

who is expected to take the next turn [72.143, 167–171].

Researchers have also been well aware of the importance of the time-sensitive nature of communication. For instance, interruption in the middle of a speaker's turn has also recently been taken into account in dialog management systems [72.164, 172]. *Chao* and *Thomaz*, proposed more elaborated model, in which time-synchrony in verbal and nonverbal cues, e.g., gaze and gesture, are addressed using a Petri-net-based representation [72.173]. Empirical studies have revealed what is good synchrony and timing. For instance, *Yamamoto* and *Watanabe*, have studied synchrony within a robot's utterance and motion, and revealed that people prefer the robot whose utterance is slightly delayed from the start of its motion [72.174]. This would mirror what humans do everyday, as it is reported that humans' gestures are performed slightly ahead than their utterances [72.175]. *Shiwa* et al. revealed that people prefer small delay in the robot's response, and conversational filler such as *etto* would be useful to buy time when the robot's response is delayed ([72.176] and VIDEO 806).

However, while above studies are under the assumption that information is communicated through turn-based dialog, recent studies have revealed more dynamic cases of human–robot communication, in which the way robots communicate information is sometimes out from the turn-based dialog paradigm. For instance, during the moment a robot and a person are going to initiate interaction both of them communicate their intention that they would like to meet and talk. A couple of studies investigated a way for a robot to express its intention to welcome the initiation of interaction [72.177]. When the target user is seated, *Dautenhahn* et al. revealed that they prefer the robot approach from side ([72.178] and VIDEO 258). Figure 72.9 shows a scene in which the robot approached to pedestrians. *Satake* et al. revealed that such interaction failed if the robot failed to communicate its intention to talk. As the robot was operated in noisy shopping mall, when it used only verbal utterance, the robot was simply ignored. Instead, they found that the robot needs to communicate its intention nonverbally. It needs to approach from a frontal direction and needs to be responsive in adjusting its body orientation toward the targeted person; such nonverbal behavior made the robot more success in initiating conversation with pedestrians [72.179].

Pedestrians also communicate their intention nonverbally; for instance, when he/she does not wish to talk to the robot, they avoid approaching to the robot. Thus, a robot could use the proximity information to estimate people's willingness in initiating interac-



Fig. 72.9 A robot that approaches pedestrians

tion. Michalowski et al. classified spatial zones around a robot, and let the robot talk to the person if he/she approached to the robot and entered to social distance [72.177]. There are some empirical studies about proxemics that revealed that people often prefer to stay at social distance when they talk to a robot [72.180–182].

Joint attention (as introduced in earlier Sect. 72.4) can be silent. Figure 72.10 and VIDEO 257 show a scene where a person share his attention target nonverbally with the robot. The person is curious about the computer and stands in front of it; then, the robot moves to the location convenient to explain the object. When the person moves to the other exhibit, the robot follows him and explains the one in front of him. Here, it is their standing position that communicates the target of attention [72.183, 184].

These examples show the cases where communication is not necessarily turn-based. This is because information can be exchanged nonverbally in such casual communication. Unlike the speech channel that needs to be typically occupied by only one speaker (speaking person), nonverbal signals can be mutually exchanged at the same time. For instance, when a pedestrian and a robot meet, their positions continuously change while they walk which communicates whether they would like to initiate conversation. As so-

cial robots aim to operate in people's daily environment, such a casual and nonverbal exchange of information is not a trivial part of human–robot communication. The research for fully unveiling required mechanism for such continuous exchange of social signals is still premature.

On the other hand, some studies started to highlight the needs of a mechanism that connects communication and background knowledge. It is revealed that the model of common ground makes daily communication effective [72.185]. For example, a direction-giving scenario would be a case where environmental knowledge is useful. For instance, when a robot provides directions (Fig. 72.11 and VIDEO 259), it could be more comprehensive if the robot is aware of a visible landmark so that it could say *please turn at the book store* instead of saying *please turn at the third corner* [72.186]. Thus, a good model of environment, e.g., [72.187], would greatly improve a robot's capability in communicating about a route. Moreover, if a robot has a model of users' memory of location, it could provide destination-based direction, such as *a café is nearby the book store you just visited* [72.188], which is much easier to comprehend than complex turn-by-turn destination like *to go to a café, please turn right at first corner, turn left at third corner, and ...*



Fig. 72.10 A person and robot implicitly share the target of attention via spatial formation



Fig. 72.11 A robot that provides directions (after [72.189])

72.6.3 Challenges

To summarize, turn-based conversation has been studied to a certain degree. However, social robots often engage in casual communication in which robots would need to deal with social signals and background knowledge. Here, we denote a couple of key challenges.

Revealing Repertory of Communication Skills

Previous studies started to reveal different forms of communication where various perceptual and cognitive capabilities are required. Early studies have revealed the importance of social signal processing, like recognizing and expressing gaze and facial expressions. Studies about initiation of conversation have revealed the mutual real-time exchange of information via their positions. Studies about giving direction

demonstrated further needs of associating language and environmental knowledge, e.g., a *cognitive map*, how people perceive environments, and remembering landmarks.

To what extent do we need to cover repertoires? We believe that there could be many elements we will find. Many of them might be interrelated with perception and cognition. Such a case would improve our understanding about what communication skills truly are. Thus, one of the important challenges is here.

Architecture for Communication Skills

Along with finding out the repertory of communication skills, the other important challenge is to deal with the integration, i. e., the architecture of communication skill. Moving from a turn-based structure to a dynamic structure is the real challenge.

72.7 Long-Term Interaction with Robot Companions

A number of social robots have been introduced as companion robots. Companion robots may have the sole purpose of providing companionship, e.g., in studies using toy robots such as the Pleo [72.190], but often they combine two aspects: *being useful*, i. e., being able to carry out certain tasks for the user, and carrying those tasks out in a manner that is socially acceptable [72.191]. The latter notion has been used, e.g., in several European projects [72.192–195]. The notion of a companion often entails repeated and long-term interactions. This poses particular challenges not only for the design of the robot, the interaction design, the choices of tasks/settings/scenarios, but also on the how to ensure satisfactory and successful interaction with the robot.

72.7.1 Robot Companions

Recently more and more researchers are moving toward studying application areas that develop such companion robots, e.g., the use of robots in assistive and rehabilitation robotics. The use of robots to assist elderly users in their homes, with a view to extend the period they can stay and live independently in their own homes, is currently being studied extensively by different research groups worldwide. Several companies are also marketing their robots as such assistive companions, e.g., the Wakamaru robot (Mitsubishi Heavy Industries Ltd) that was introduced in 2005, or the Human Support Robot (Toyota) revealed in 2012. In addition, numerous research prototypes exist, e.g., Cody (Georgia Tech), Herb (CMU), Care-O-bot 3 (Fraunhofer), Hector (CompanionAble project).

A number of tele-presence robots have been developed, but this chapter will focus on autonomous or partially tele-operated companion robots. Note, Cody targets the domain of patient hygiene care that is related to issues discussed in the section on tactile human–robot interaction. Regardless of whether human–robot interaction with companions include tactile interaction, or is a hands-off approach (Chapt. 73), developing such system involves a careful study of the roles and functions of such robots in the application domain, and of users’ perception of and attitudes toward such a system.

Figure 72.12 and  VIDEO 218 show the Care-o-bot robot (Fraunhofer) used in the ACCOMPANY project on home assistance for elderly people. The robot is shown in the University of Hertfordshire’s Robot House, a domestic setting for experiments into robot home assistance where participants regularly visit for human–robot interaction sessions. Such *living lab* settings are increasingly being used to design, experiment and evaluate innovative systems (e.g., the European Network of Living Labs, [72.196]). Providing such environments facilitates progress toward complex robotic systems that can be deployed in real-life environments.

72.7.2 Engagement and Long-Term Relationships

The concept of a robot companion entails repeated, long-term interactions, which may also afford the development of *relationships* between robots and people. Relationships with robots can take many shapes and forms, and the formation of relationships will be influenced by many factors. For example, the specific

role of the robot (Butler? Friend? Tutor? Assistant? Tool? etc., [72.197]) will matter, as well as the robots' specific embodiment and behavioral and expressive repertoire that is often used to present them as *relational artifacts* [72.198, 199] that are designed to build and maintain social-emotional relationships with users.

Many applications with social robots do only involve short-term interactions, e.g., robots meant to function as a museum guide [72.200] and  VIDEO 808, a receptionist, etc. Here, the *novelty effect* can often be exploited, i.e., the general interest that many people have in new robots. However, after repeated interactions this effect can wear off and people can lose interest in a robot. Thus, a main research challenge is how to keep people engaged in the interaction and keep them motivated to interact with the robot. Establishing a useful and enjoyable relationship with a robot is not an easy task. And what exactly is *long-term*? Tanaka et al. [72.22] mentions at *10-hour barrier* (total interaction time), Sung et al. [72.201] pose the goal of long-term interaction over more than 3 months as a main challenge. Hüttenrauch and Severinson-Eklundh [72.202] performed a user study with the service robot CERO meant to assist one user over three months in an office environment. Kanda et al. [72.189] and  VIDEO 809 investigated a partially tele-operated robot over a 25-day period. The nature of these interactions depends on whether studies take place in a school, a home, a public place, etc. It will also depend on the frequency and duration of the interaction, e.g., how many interaction episodes per time interval does an individual have with the robot?

There is also the issue of quantity and quality of interaction that may be realized very differently in different application areas of social robots. More and more studies are bringing robots into the *wild* [72.203].  VIDEO 564 shows how preschool age children interacting with a storytelling learning companion robot during repeated encounters over a 2 month period. Personalization of the robot stories to the children led to improved vocabulary learning. Field studies are often said to be preferable, and more ecologically valid than data collected in the laboratory. However, practical, technical, and methodological constraints may limit the length and nature of the field studies. Also, bringing a robot in the *wild* does not necessarily make the interactions with people more natural, and the more *messy* conditions pose hard methodological problems and can often interfere with controlled data collection and statistical data analysis [72.204]. A field study by Heylen et al. [72.204] placed a simple dialogue Nabaztag (rabbit) robot in a few people's homes over 10 days, and it illuminates a number of those real-life problems with

field studies which impacts on the validity of the results that can be gained and on the user experience. The latter will then ultimately decide on whether people will consider a long-term companion robot *amusing or a nuisance* [72.204]. A taxonomy to characterize studies in the *wild* for child-robot interactions is provided in Salter et al. [72.205]. Systematic analyses of different experimental conditions and tasks, settings, etc., whether in the laboratory or in field studies, will help the planning, design and comparison of different long-term studies.

Note, often the expectations of users are not met by the robot's design and abilities, and nor does it fit into daily activities of users [72.190]. The advancement of robot technology and knowledge of HRI will enable more and more field studies, in schools [72.206], nurseries [72.22], private homes [72.190], care homes [72.31], etc.

In many of the above long-term studies, commercially available robots have been used. The reasons for this are not only availability, but also robustness and reliability, as well as safety. The use research prototypes in field studies should always entail securing Institutional Review Board (IRB) approval to meet ethical guidelines when human participants are involved. Even prototypes that are generally safe to use, may still have *cables sticking out*, etc. Hence often it is a necessity to have researchers present at all times during these studies. Research prototypes are also by their very nature more prone to break down, and again this requires the constant attention of researchers. The design of research prototypes is also often not ideally suited for a field study, e.g., wheels when being used on cluttered surfaces, etc. Interesting insights on those *practical* but nevertheless very important points can be found, e.g., in Hüttenrauch et al. [72.207] where a modified Peoplebot (Mobile Robotics) robot was brought into eight different homes for approximately 1 hour each in order to study spatial management in HRI situations. Note, even when leaving a robot alone with a person or family in their own home, people may still be acutely aware of the *experimental* nature of the interaction [72.204].

Establishing and maintaining relationships between users and robots in long-term interactions needs careful consideration, and many insights can also be gained from related long-term studies with virtual agents, e.g., as exercise advisors [72.208, 209].

72.7.3 Robot Home Companions for Supporting Elderly Users

Several HRI studies in the home focus on the use of a companion robot for the general population. Koay et al. [72.210] report on a long-term, 5-week study

in a domestic environment with a partially remote-controlled robot involving several different scenarios (e.g., a collaborative task, sharing physical space, recording and revealing personal information, interrupting a person to serve them, and seeking assistance from a person using combinations of physical and verbal cues). The results highlight concerns and expectations that people have in such scenarios that are relevant for the domestic use of robots. Note, the robot used in this study was partially remotely controlled, which allowed the investigation of complex scenarios.

Due to demographic changes, a lot of interest exists worldwide into developing robot technology for the care of elderly people that would allow elderly people to remain in their own homes for longer, or to provide assistance in sheltered or otherwise specifically designed environments. A robot may assist an elderly person in the home in different ways, e.g., provide physical assistance (standing up, walking, fetching and carry objects, etc.), social assistance (e.g., engaging the user in interactions with other people) and cognitive assistance (e.g., reminder functions).

In HRI, there is prior work investigating robot's ability to remind users of future or prior activities. Autominder using the Nursebot represents an initial attempt to make reminders more intelligent and dynamic [72.211]. Intelligence and dynamics were also key aspects of the system proposed by the Robocare project [72.212]. More recently, the KSERA project [72.213] focused on the ability of the robot to draw on information not readily available to the user as well as its ability to persuade in order to safeguard the health of the user. Other examples for assistance and reminders for elderly people with dementia through multimodal interactions and smart-house integration include the EU FP7 CompanionAble project and the MOBISERV project [72.214]. The project, Florence [72.215], introduces a commercially available robot as an autonomous lifestyle device for ambient assisted living; it provided multiple services to users including an agenda reminder application that allowed the elderly to share information with caregivers, etc. The European projects SRS [72.216] and ACCOMPANY [72.217] both use the care-o-bot 3 (Fraunhofer) (Fig. 72.12) as their target robotic platform. While SRS involves the use of the robot in a remote-control scenario, the ACCOMPANY project develops fully autonomous behaviors for an empathic and assistive home companion.

Several projects combine a robotic companion with an intelligent smart/ambient environment as part a variety of ambient assisted living (AAL) solutions to assist with older adults, or people with disabilities, to live independently by providing support in activities of daily

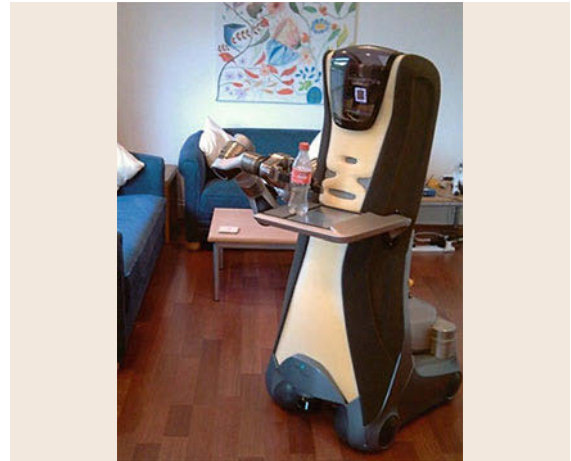


Fig. 72.12 Care-O-bot 3 robot (courtesy of Fraunhofer)

living (ADLs). Such topics are currently being studied world-wide. See, e.g., the quality of life technology (QOLT) [72.218] Centre of Carnegie Mellon University or the Centre for Affective Solutions for Ambient Living Awareness (CASALA) [72.219].

72.7.4 Example: Long-Term Interactions with a Robotic Weight Loss Coach

A number of recent studies investigate the use of robotic companion as health *coaches* or *advisors*. Kidd and Breazeal developed Autom [72.116, 220] (VIDEO 558), a robot specifically designed for long-term interaction with people in the role of a robotic weight loss coach. Autom has a clear function and role, but also needs to interact with users in a socially acceptable and comfortable manner, so that users intuitively understand the robot, are willing to engage with the robot, and *listen* to it. This robot is also an example how academic research in long-term HRI can lead to new innovations and commercialization. The main purpose of the robot is to help the user to lose weight, trying to persuade the user to change his or her behavior [72.221].

A key ingredient supporting this functionality is the creation of a relationship between the user and the robot. Autom is thus an example of a robot that presents itself as a relational artifact and encourages people to develop social-emotional relationships with them [72.198, 199]. Autom uses a psychologically inspired relationship model, with the robot's role as a caregiver. It engages the use in a dialog modeled after patient-care professional dialog to provide social support (Sects. 72.5.4 and 72.5.5) in order to build a working alliance as well as to be helpful, persuasive, positive, and supportive. For a health care coaching robot, where behavior change is a central objective,

such a relationship is very important. People who need to lose weight typically do not lack the intelligence or knowledge necessary to understand that weight loss would improve their health and general well-being. The motivational factor is often a crucial point, so a weight loss robot's role on providing social support is different from that of a kiosk robot only needs to provide information.

A long-term study with 45 participants an Autom prototype robot over 6 weeks was the first study designed to create behavior change in people with a weight management goal (Fig. 72.13). The results were very encouraging: participants developed a close relationship with the robot, and they tracked their calorie consumption and exercise much longer when using the robot, compared to other methods (a computer running the same dialog or a paper log for manual entry). Since these factors are indicators of longer term weight loss success, the study provided evidence for the effectiveness of sociable robots for long-term HRI [72.116].

72.7.5 Challenges

Many of the projects studying the use of robot companions (e.g., supporting elderly users, providing assistance in therapy, or helping in office environments) are still at an initial stage. Future results from extensive, long-term, multi-site and even cross-cultural evaluation studies are still needed in order to illuminate the usability, usefulness, and acceptability of such systems. It is particularly advantageous if the same research platform is used in different projects so that direct comparisons and the sharing of research developments are possible.

The challenges of supporting engagement in long-term studies are beginning to emerge. New sensors and interfaces, such as brain-computer interfaces, could provide richer information on people's emotional, attentional engagement states when interacting with a robot. Robots are providing richer social cues to explore the whole spectrum of human-human interaction modalities, e.g., using gaze, gesture, proxemics, dialogue, contingency, etc. [72.177, 222–226]. Measuring engagement in real time and allowing a robot to respond to it is a key challenge. In a user study with 37 participants and a robot that could perceive user engagement Sidner et al. [72.32] found that engagement gestures were perceived more positively than a robot without such gestures. Rich et al. [72.139] proposed an initial computational model for a robot to model engagement, based on the recognition of different events involving gesture and speech.

A clear framework of what engagement means in HRI in general, and for long-term HRI interactions



Fig.72.13a,b Autom, a weight management and exercise coach. (a) The Autom prototype robot developed at MIT; (b) the commercial version of the Autom robot

in particular, is needed and will need to be validated in extensive testing. Several other proof of concept studies of robots that adapt to user engagement and interaction show encouraging results. François et al. [72.227] evaluated a robot that adapts to user interaction in a therapeutic context based on tactile information (how children touched the robot), while Szafir and Mutlu [72.228] demonstrated how a robot can adapt to the engagement of the user, utilizing techniques from brain-computer interfaces in order to assess engagement. Future applications of this research into adaptive robots target educational settings where a teacher robot can automatically adapt to the pupils' engagement, or therapeutic/rehabilitation applications where the robot can automatically adapt to the patient's needs and preferences in light of therapeutic objectives.

Future research needs to illuminate how best to design interaction and embodiment of social robots that are successful in long-term interactions with people. Since adding social interaction skills to a robot is costly, the identification of a set of robot characteristics (appearance, behavior, cognition) that are necessary and sufficient to create meaningful, acceptable, and efficient long-term interaction with a robot would be beneficial. Here, it is important to provide frameworks that connect to empirical methodologies, cf. the discussion of a conceptual and methodology framework for robot believability in Rose et al. [72.229]. Note, while predominantly humanoid or zoomorphic robots are currently being used in long-term HRI experiments, even mechanically looking robots such as the Roomba robot may invite people to develop a social-emotional relationship with its users [72.201, 230].

Using robots in long-term repeated interactions with people also involves a number of ethical issues, as it has already been highlighted also for embodied conversational agents and virtual characters [72.208]. While in some applications the robot may have a useful function if portrayed as a care-receiver [72.133], in most applications the companion robot should provide

care to its users [72.191]. As pointed out by *Turkle* et al. [72.198, 199], robots that present themselves as relational artifacts may influence people's understanding and expectations of the nature of social relationships and friendship. Ethical issues are particularly important when users are vulnerable people such as adults with special needs, elderly people, or children. Many researchers have commented on these issues [72.231, 232].

Practical issues can also become crucial to the acceptance of a robot for long-term interaction, as it has been highlighted in a long-term study with *Pleo* – a commercially available robot, but which requires maintenance that does not fit easily into people's routines [72.190]. *Fernaes* et al. also bring up the important issue of interaction design that needs to support

long-term interaction, an issue that was also brought up in user feedback from the participants in their long-term study. Novel approaches to how to design human–robot interaction may be required to facilitate long-term use of companion robots [72.190], and in real-world settings attention must be paid to how the robot technology is being introduced to people and how people and robots must adapt to each other [72.230].

Recently, the blending of virtual and robotic characters area a growing area of research whereby seamless transitions from a virtual to and from a robotic character [72.233], or migration between different robot and other digital embodiments [72.234] pose interesting challenges for future long-term companions. Indeed, it may change the nature of what we usually perceive as a *companion robot* [72.148, 233, 235–242].

72.8 Tactile Interaction with Social Robots

In robotics and artificial intelligence research, tactile interaction has long been exploited primarily as a necessity to enable, e.g., collision detection, grasping and object manipulation, particularly in combination with vision and other sensor modalities, and led to adding touch sensors to a robot's gripper or hand [72.243].

72.8.1 Touch for Social Interaction

However, the importance of *human–robot* tactile interaction has been highlighted recently in a number of research projects, inspired by evidence from human–human interaction and child development. The recent interest in the *sense of touch* goes beyond the necessity of touch for interactions with the physical environment, but focuses on the important role of tactile interaction in interactions with the social environment. For instance, *Siegel* et al. [72.244] found that social touch, such as shaking hands, can impact how persuasive a robot is perceived to be [72.244]. In other work, the same kind of touch can have a different impact on people's response to the robot depending on the context [72.245].

Indeed, humans are born as *tactile creatures*. Physical touch is one of the most basic forms of human communication. In human development, touch plays a crucial role in developing cognitive, social, and emotional skills, as well as establishing and maintaining attachment and social relationships. Deprivation of touch in early child development can have devastating effects on a child's development [72.246]. A comprehensive survey on communicative functions of touch in humans and other animals can be found in *Hertenstein* [72.247].

72.8.2 Touch Sensors and Mechanisms Used for HRI

Recently, more and more social robots are being equipped with tactile *skin*, thus allowing the robot to react according to the person touching the robot. Recent trends, e.g., in the European project *Roboskin* [72.248] tend toward covering the whole, or most of the robot's body, see e.g., *Schmitz* et al. [72.249] for an example using modular capacitive sensors to cover the humanoid robot *iCub*. Related work by *Dahiya* et al. [72.250] surveys a variety of different technological approaches toward tactile sensors and mechanisms of tactile sensor for robots. They show how one may take inspiration from biological tactile sensors in humans and derive design hints for robotic tactile sensing. *Stiehl* et al. [72.251] designed a tactile system inspired by the human skin as well as somatic processing [72.251], and was later developed to recognize social and affective communicative intent of how a human touches the robot [72.252, 253]. The new compliant skin technology developed in the *Roboskin* project has two primary functions: (a) to allow a robot to operate safely and efficiently, and (b) to use tactile sensors for communication, interaction, and cooperation with people.

The field of tactile human–robot interaction is indeed a growing area of research, and a recent survey discusses tactile *HRI* from the perspectives of the types of interactions that may occur between a robot and a human, and the types of sensors that allow to detect these interactions in various robotic systems such as the *Robovie* series of robots, *RI-MAN*, the *Hugable* robot [72.253], or *Paro* [72.254]. Note, equipping

a robot with tactile sensors may add its functionality, but in some cases the *sense of touch* is crucial for the key functionality of the robot (e.g., in the case of Paro [72.251] with a therapeutic/care function, or in the case of the Huggable to improve social relationships [72.255]). Many toy robots built primarily for human–robot interaction have touch sensors for petting and stroking, e.g., the AIBO or more recent Pleo robots. Indeed, the use of tactile HRI to support human–human communication over the distance is a promising area of research [72.255–258]. Tactile feedback can also improve teaching a robot by demonstration [72.259].

In order to realize robots' capability of a *sense of touch*, there are difficult sensor processing and perception problems to be addressed. One problem is that we need to identify the geometrical relationship between a number of sensors embedded in a whole body of a robot and body parts being touched when sensors are activated. For better perception of various touching, one can embed sensors into or under a soft skin. For instance, Robovie II-F has 274 sensor elements (Piezofilms) embedded in soft silicone rubber (Fig. 72.14). Tactile action activates multiple sensors at the same time, thus nearby sensors are all activated when touch action occurs to one place of body. For this problem, Noda et al. [72.260] took a bottom-up approach using observed signal patterns. Their method works in a self-organizing manner to identify mapping between signal patterns and touched location.

The second problem is the semantic relationship between signal pattern and people's communicative intention of touch action. For instance, Tajika et al. [72.261], applied clustering method for signal pattern to retrieve hierarchical structure of haptic actions. For instance, tickling-chest (Fig. 72.15) is found to be similar to stroking-chest, grouped together as lightly touching-chest action. Knight et al. [72.262] developed an algorithm based on identification of typical touch types, such as tickle, pet, and poke. Yohanan and MacLean [72.263] categorized humans' intent to communicate affect state and mapped touch action to each category, for example, comforting intent is mapped with actions like stroke and pat. Stiehl and Breazeal [72.264] trained a neural net to classify touch according to affect and communicative intent by recognizing types of socio-affective touch (e.g., pleasant or unpleasant ways of touching or teasing based on the way a person tickles, touches, pats, slaps, rubs, squeezes, etc.)

François et al. [72.227] describe an algorithm for pattern recognition in HRI, the cascaded information bottleneck method and apply it to real-time autonomous recognition of human–robot tactile interaction styles. This method uses an information theoretic approach

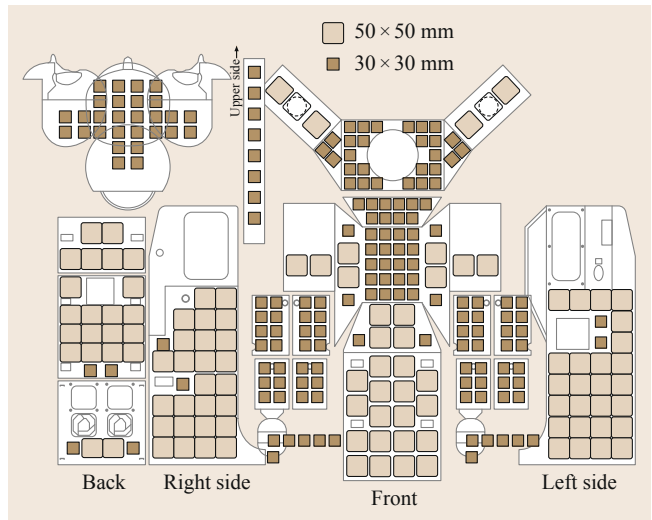


Fig. 72.14 An example of layouts of piezofilm sensors embedded in a soft skin (left)



Fig. 72.15 A child tickling the chest of a robot

and enables to progressively extract relevant information from time series. An evaluation with real interaction data obtained with a Sony AIBO robot shows that the algorithm is capable of classifying interaction styles (frequency and gentleness of the interaction), with a good accuracy and a very acceptable delay. The cascaded information bottleneck method was later successfully applied to create a socially adaptive robot that can recognize and adapt to children's play styles in real time [72.265]. The robot rewards well-balanced interaction styles and encourages children to engage in the interaction. The potential impact of such an adaptive robot in robot-assisted play for children with autism is evaluated through a study conducted with seven children with autism in a school. A statistical analysis of the results shows the positive impact of such an adaptive

robot on the children's play styles and on their engagement in the interaction with the robot.

72.8.3 Example: Teaching Children with Autism About Tactile Interaction

Using robots for the therapy and education for children with autism was first proposed by *Kerstin Dautenhahn* [72.266, 267] and it has recently attracted a lot of attention in the research community. A number of such approaches focus on *robot-assisted play*, since play has a crucial role in a child's development. During play, children can learn about themselves and their environments as well as develop cognitive, social, and perceptual skills. Autism, or better autistic spectrum disorders (ASD), is a life-long development disorder with key impairments in communication and social interaction and imagination (DSM IV, 1995) [72.268, 269]. Robots allow for a simplified, predictable, and reliable environment, where the complexity of interaction can be controlled and gradually increased [72.270]. Children can play dyadic games with robots, or triadic games involving other children or adults. In the latter case, scenarios emphasize the role of the robot as a *social mediator* or [72.271].

Robot mediated playing and learning activities, if successful, have the potential to enable children with cognitive disabilities to learn and acquire basic social skills thus getting support to develop/enhance their individual potential especially in the areas of communication and interaction [72.270, 272]. A number of different social robots have been studied in this domain, including zoomorphic robots, humanoid robots, or mechanically looking robots, e.g., Labo-1 [72.273], NAO [72.274], Probo [72.275], Robota [72.276, 277], Keepon [72.278], Aibo [72.279], Tito [72.280], KASPAR [72.21], and others. While we find encouraging results from case-study evaluations, further long-term and clinical studies are required [72.281].

Diehl et al. [72.281] in their review on the clinical use of robots for individuals with autism suggested that the use of interactive robots is a promising development in light of the research showing that individuals with autism exhibit strengths in understanding the physical world and relative weaknesses in understanding the social world. Children with autism often find it very difficult to appropriately interact with their social environment. In interactions between children and their peers, teachers, and family, usually touch has an important communicative and emotional role.

However, children with ASD may be hyposensitive or hypersensitive to touch so that the children may crave or avoid touch. As part of the above-mentioned Eu-

ropean Roboskin, a number of case study evaluations have been performed investigating how a humanoid robot equipped with touch sensors can teach children with autism about appropriate tactile interaction and the associated emotional responses. The studies used the child-sized, minimally expressive robot KASPAR [72.21]; [72.282]), a low-cost robot specifically designed for interaction – many of its features lend themselves to children with autism, e.g., the human-like but minimally expressive shape and form of the robot. The robot has 8 DOFs (degrees of freedom) in the head and face and 6 DOF in each arm, as well as one DOF in the torso. A comprehensive set of play scenarios for robot-assisted play for children with various special needs, and tactile play scenarios for children with autism have been developed [72.283–285].

KASPAR can play a variety of games with children, either operating completely autonomously [72.285, 286] and  VIDEO 220, or being partially remotely controlled by the children or an adult as part of the play scenario. Case studies on tactile child–robot interaction have shown encouraging results (*Robins et al.* [72.283, 287]). In the research on tactile interactions KASPAR was equipped with patches of tactile sensors, and it produced some responses autonomously, e.g., a ticking of the chest resulted in laughing, or hitting in the face results in the robot turning away from the child, covering its face with its hands and saying *ouch, that hurts*. If the child touches areas that are not covered by skin patches, or if the recognition of different types of touch is not reliable enough [72.288], then the experimenter can trigger the robot's reaction.

Figure 72.16 shows a child with autism first hitting the robot's leg and then exploring the robot's reaction. Since the legs cannot detect forceful touch, the experimenter triggers the robot's reactions. Note, this hybrid approach of autonomous behaviors combined with a remote control allows the robot to be perceptually more advanced than current state-of-the-art robotics sensing technology allows. Robots used with children with autism need to be predictable, and so a mistake in the robot's sensing abilities can be compensated for by the adult present (experimenter, teacher or caregiver). A person who knows the child very well will also be able to trigger certain useful robot behaviors at certain movements in time which are not observable directly from the child or the context and can only be inferred from detailed knowledge about the child, his/her needs and preferences, and therapeutic goals and objectives for this particular child.

Note, for a robot to detect and respond to tactile interactions of children with autism is not only beneficial to teach about appropriate tactile interaction, but it can

also provide a basis for adapting to a child's individual interaction style [72.265].

Tactile interaction is often not the sole focus of interaction, it can be embedded in multimodal play scenarios with the therapeutic objective to increase children's social skills through play. François et al. [72.279] present a long-term study where six children diagnosed with autism interact with an autonomous zoomorphic robot (Sony Aibo) over 10 sessions. The study is inspired by nondirective play therapy to encourage children's proactivity and initiative-taking. The behavior of each child is analyzed in detail according to three dimensions (play, reasoning, affect). Unique trajectories for children's progressions along these three dimensions were observed, resulting in unique profiles. The work highlights methodological issues in the domain of robot-assisted therapy, and also points out and formalizes different potential roles of the experimenter in the sessions, who may be a passive or an active participant [72.289]. A regulation process is introduced whereby the experimenter can regulate the interaction under specific conditions in order to:

1. Prevent or discourage repetitive behaviors
2. Help the child engage in play

3. Give a better pace to the game if it has already been experienced by the child
4. Bootstrap a higher level of play, and
5. Ask questions related to reasoning or affect.

72.8.4 Challenges and Opportunities

While many studies assume that tactile HRI will result in a more enjoyable, meaningful, and efficient interaction with a robot, many issues are still unclear and need to be investigated further. For example, a video-based study, where participants watched videos of interactions rather than interacting with the robot themselves, showed the impact of a robot's level of autonomy, and suggests that touch behaviors are considered more appropriate for proactive as compared to reactive robots [72.290]. Much further research is needed to find out when and how tactile interaction can enhance a person's experience of interaction and benefit the overall performance of the human–robot triads. One can also expect that individual differences will play a role in which types of tactile interaction with a robot are more appropriate, depending also on the tasks involved and the overall context and setting. The perception of people in terms of the robot's roles and its



Fig. 72.16 (a) Child hits the robot's leg and then explores the robot's reaction. (b) The child sees the robot looking sad, so he tickles its tummy (left) to make it happy (right). (c) The minimally expressive humanoid robot KASPAR

relationship with its users is also likely to impact these issues.

In recent years a number of projects worldwide have tried to use robots for therapy of children with autism. Different modes of robot control and autonomy need to be investigated, from fully autonomous systems [72.285], to Wizard-of-Oz controlled robots [72.291], to using a hybrid approach where remote control is an integral part of the interac-

tion and triggers autonomous behaviors [72.287, 289]. Realistically, for therapeutic tools to be used widely outside the laboratory and the experimental setting, the technology needs to be highly robust, reliable, easy to operate by nonresearchers as well as cost-effective.

A number of technological, methodological, and design challenges still need to be tackled, but tactile interactions with social robots open up a number of new research avenues as well as exciting applications.

72.9 Social Robots and Teamwork

Verbal and nonverbal communication play a very important role in coordinating joint action during collaborative tasks. Sharing information through communication acts is critical given that each teammate often has only partial knowledge relevant to solving the problem, different capabilities, and possibly diverging beliefs about the state of the task. For instance, all teammates need to establish and maintain a set of mutual beliefs regarding the current state of the task, the respective roles and capabilities of each member, and the responsibilities of each teammate [72.33, 153]. This is called *common ground* [72.162].

72.9.1 Human–Robot Teamwork and Collaboration

Dialog certainly plays an important role in establishing common ground. Each conversant is committed to the shared goal of establishing and maintaining a state of mutual belief with the other. To succeed, the speaker composes a description that is adequate for the purpose of being understood by the listener, and the listener shares the goal of understanding the speaker. This communication act serves to achieve robust team behavior despite adverse conditions, including breaks in communication and other difficulties in achieving the team goals.

Humans also use nonverbal skills such as visual perspective taking and shared attention to establish common ground with others. They orient their own gaze and direct the gaze of their teammate through deictic cues such as pointing gestures in order to establish common ground. Given the visual perspective taking, shared attention, and the use of deictic cues to direct attention are core psychological processes that people use to coordinate joint action about objects and events in the world, robot teammates must be able to display and interpret these behaviors and cues when working with humans in a manner that adheres to human expectations.

Breazeal et al. [72.142] investigated the impact grounding using nonverbal social cues and behavior on task performance by a human–robot team. In a human subject experiment, participants guided Leonardo to perform a physical task using speech and gesture. The robot communicates either implicitly through behavior (such as gaze and facial expressions) or explicitly through nonverbal social cues (i.e., explicit pointing gestures). The robot's explicit grounding acts include visually attending to the human's actions to acknowledge their contributions, issuing a short nod to acknowledge the success and completion of the task or subtask, visually attending to the person's attention directing cues such as to where the human looks or points, looking back to the human once the robot operates on an artifact to make sure its contribution is acknowledged, and pointing to artifacts in the workspace to direct the human's attention toward them. Both self-reporting via questionnaire and behavioral analysis of video support the hypothesis that implicit nonverbal communication positively impacts human–robot task performance with respect to understandability of the robot, efficiency of task performance, and robustness to errors that arise from miscommunication [72.142].

Common ground is grown along with partners that work together over time. In a simple example, if two persons repeatedly work in a sequence of collaborative manufacturing tasks, one will be able to easily predict what the other person will do next and thus proactively help each other. For instance, if one always needs a spanner to be passed at certain moment in the task, another person will probably take anticipatory action passing the spanner before being asked. *Hoffman* and *Breazeal* developed adaptive system that learn such task structure which enabled a robot's anticipatory action [72.292]. They further revealed the importance of perceptual simulation [72.293].

The importance of such common ground and cognitive similarity is demonstrated in partnership in casual social interaction too. For instance, *Morales* et al. re-

vealed that a robot efficiently performed side-by-side walking with a human partner when it anticipated where a human partner would walk [72.186]. Such anticipatory computing was enabled by a capability of computing a preferred walking course in a similar way as humans would do. There are robots that explicitly learn common knowledge, like one that learns names of places [72.294].

72.9.2 Robots as Social Mediators

Researchers have started to explore the use of robots as a *social mediator*. One approach is to use a human-like presence of robots as social stimuli. It is known that presence of people facilitate others. For instance, people perform simple math-calculation faster when being watched by someone else. This is known to be *social facilitation effect* [72.295]. Riethe et al. [72.296] reported that people's performance on easy math-calculation is improved because of presence of robots [72.296]. Takano et al. [72.297], put an android robot as a bystander where patients meet a medical doctor in a hospital, and found that it moderated clients' anxiety and let them believe that the doctor pays more attention to them [72.297].

Another approach is to use a robot as an active coordinator in humans' social settings. When there are many people, a coordinator could make their activity more efficient. Such a role can also successfully replicated by a robot. Consider the situation where an interactive robot is placed in the middle of a group of kids, and they start to push each other away when they want to play with the robot differently from each other. Shomi et al. [72.298], developed a technique to identify when crowd of people around a robot is disordered, and let the robot perform attention-controlling behavior so that children play together with the robot in coordinated way [72.299] (Fig. 72.17). In other work, robots have



Fig. 72.17 The robot interacted with a crowd of people with coordinating their attention

been used to facilitate elderly people's group conversation. Matsuyama et al. [72.300], developed a robot to participate in a quiz game, conducted as a recreation activity in elderly-care facility, and provide inspiring answer to facilitate other elderly people to continue the game [72.300]. In these works, robots actively model the social situation and intervene in people's activities based on its understanding of the situation.

72.9.3 Research Direction

Human activities are often social, involving multiple people who often have different skills, desires, and goals. Although the research is only in an early stage we have started to model such social situations while revealing potential roles of robots in such social settings. Along with further advance of relevant technologies, e.g., manipulation capability, navigation capability, and language capabilities, there should be many potential uses to be unveiled. However, it is most likely that the underlying theoretical work still needs a lot more work as well.

72.10 Conclusion

In this chapter, we have presented some of the principal research trends in social robotics and human-robot interaction. We have relied heavily on examples from our own research to illustrate these trends, and have used excellent examples drawn from other research groups around the world.

From this overview, we have shown that one of the most important goals of social robotics as applied HRI is the creation of robots that are human-compatible and human-centered in their design. Their differences from human abilities should complement and enhance

our strengths and support how people help one another. Their similarities to human abilities, such as computationally implementing human cognitive, affective, or multimodal communication models make them more intuitive for people to understand and interact with. Further, such robots are also being used as a scientific tool to help us to understand ourselves better. With this broadening understanding, social robots are being designed to offer increasingly sophisticated levels of social, affective, cognitive, and task-based support for people, opening new applications for robots

in education, health, therapy, communication, domestic tasks, physical tasks requiring coordination and teamwork, and more. As the field advances, social robots are being applied to increasingly sophisticated tasks, in increasingly complex human environments,

for longer deployment periods. We expect that in the coming decades, many other researchers, especially young researchers, will actively contribute to the transition from today's robots into capable robot partners of tomorrow.

72.11 Further Reading

For further reading, we recommend the following conference proceedings, journals, books, articles:

- Annual conference proceedings:
 - Proceedings of the ACM/IEEE International Conference on Human–Robot Interaction (HRI)
 - Proceedings of the IEEE International Symposium on Robot and Human Interactive Communication (ROMAN)
 - AAAI Symposium Series
 - AISB Symposium Series
- Journals:
 - Journal of Human-Robot Interaction (<http://humanrobotinteraction.org/journal/>)
 - Interaction Studies-Social Behaviour and Communication in Biological and Artificial Systems published by John Benjamins Publishing Company
 - International Journal of Social Robotics by Springer
 - IEEE Transactions on Autonomous Mental Development (TAMD)
 - IEEE Transactions on Human–Machine Systems
 - IEEE Transactions on Affective Computing
 - Paladyn, Journal of Behavioral Robotics, de Gruyter
 - PLoS ONE

Reviews and overviews can be found in several books and articles:

- Books:
 - C. Breazeal: *Designing Sociable Robots* (MIT Press, Cambridge 2002)
 - R. W. Picard: *Affective Computing* (MIT Press, Cambridge 1997)
 - J.-M. Fellous, M. Arbib (Eds.): *Who Needs Emotions: The Brain Meets the Robot* (Oxford, Oxford Univ. Press 2005)
 - K. Dautenhahn, J. Saunders (Eds.): *New Frontiers in Human–Robot Interaction*, Advances in Interaction Studies, (John Benjamins Publishing, Amsterdam 2011)
 - T. Kanda, H. Ishiguro (Eds.): *Human-Robot Interaction in Social Robotics* (CRC Press, Boca Raton 2012)
- Review Articles:
 - T. Fong, I. Nourbakshsh, K. Dautenhahn: A survey of social robots, *Robotics and Autonomous Systems* **42**, 143–166 (2003)
 - M.A. Goodrich, A.C. Schultz: Human–robot interaction: A survey, *Foundations and Trends in Human-Computer Interaction* **1**(3), 203–275 (2007)

Video-References

- 👁 VIDEO 218 Home assistance companion robot in the Robot House available from <http://handbookofrobotics.org/view-chapter/72/videodetails/218>
- 👁 VIDEO 219 Visual communicative non-verbal behaviours of the Sunflower Robot available from <http://handbookofrobotics.org/view-chapter/72/videodetails/219>
- 👁 VIDEO 220 Playing triadic games with KASPAR available from <http://handbookofrobotics.org/view-chapter/72/videodetails/220>
- 👁 VIDEO 221 Explaining a typical session with Sunflower as a home companion in the Robot House available from <http://handbookofrobotics.org/view-chapter/72/videodetails/221>
- 👁 VIDEO 257 A robot that forms a good spatial formation available from <http://handbookofrobotics.org/view-chapter/72/videodetails/257>
- 👁 VIDEO 258 A robot that approaches pedestrians available from <http://handbookofrobotics.org/view-chapter/72/videodetails/258>
- 👁 VIDEO 259 A robot that provides a direction based on the model of the environment available from <http://handbookofrobotics.org/view-chapter/72/videodetails/259>

-  VIDEO 555 Human-robot teaming in a search and retrieve task available from <http://handbookofrobotics.org/view-chapter/72/videodetails/555>
-  VIDEO 556 Social referencing behavior available from <http://handbookofrobotics.org/view-chapter/72/videodetails/556>
-  VIDEO 557 Overview of Kismet's expressive behavior available from <http://handbookofrobotics.org/view-chapter/72/videodetails/557>
-  VIDEO 558 Overview of Autom: A robotic health coach for weight management available from <http://handbookofrobotics.org/view-chapter/72/videodetails/558>
-  VIDEO 559 Non-verbal envelope displays to support turn-taking behavior available from <http://handbookofrobotics.org/view-chapter/72/videodetails/559>
-  VIDEO 560 Learning how to be a learning companion for children available from <http://handbookofrobotics.org/view-chapter/72/videodetails/560>
-  VIDEO 562 Social learning applied to task execution available from <http://handbookofrobotics.org/view-chapter/72/videodetails/562>
-  VIDEO 563 Mental state inference to support human-robot collaboration available from <http://handbookofrobotics.org/view-chapter/72/videodetails/563>
-  VIDEO 564 A learning companion robot to foster pre-K vocabulary learning available from <http://handbookofrobotics.org/view-chapter/72/videodetails/564>
-  VIDEO 806 Influence of response time available from <http://handbookofrobotics.org/view-chapter/72/videodetails/806>
-  VIDEO 807 A scene of deictic interaction available from <http://handbookofrobotics.org/view-chapter/72/videodetails/807>
-  VIDEO 808 An example of a social robot in a museum available from <http://handbookofrobotics.org/view-chapter/72/videodetails/808>
-  VIDEO 809 An example of repeated long-term interaction available from <http://handbookofrobotics.org/view-chapter/72/videodetails/809>
-  VIDEO 810 A robot that exhibits its listening attitude with its motion available from <http://handbookofrobotics.org/view-chapter/72/videodetails/810>
-  VIDEO 811 Region pointing gesture available from <http://handbookofrobotics.org/view-chapter/72/videodetails/811>

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Multimedia Contents



73. Socially Assistive Robotics

Maja J. Matarić, Brian Scassellati

This chapter reviews the critical societal issues that have motivated research into socially assistive robotics (SAR) (Sect. 73.2) and describes the reason why *physical robots* rather than virtual agents are essential to this effort (Sect. 73.3). It highlights the major research issues within this area (Sects. 73.4–73.7), describes the primary application domains and populations where SAR research has shown an impact (Sects. 73.8–73.11), and closes with some of the ethical and safety issues that SAR research necessitates (Sect. 73.12).

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73.1 Overview

As robots become increasingly integrated into human environments, different forms of interaction are spawning new research topics and subfields. Human–robot interaction (HRI) can be broadly classified into two categories: physical and social/emotional. Physical HRI (Chap. 69) involves the research areas of manipula-

tion and haptics, among others, and is used in medical and rehabilitation robotics (Chaps. 63 and 64). In contrast, social/emotional interaction involves verbal and nonverbal expression and communication, and thus the research areas of assistive robotics, social robotics, and SAR.

Robots have long been used to provide assistance to individual users through physical interaction, typically by supporting direct physical rehabilitation (Chap. 64) or by providing a service such as retrieving items or cleaning floors (Chap. 55). Socially assistive robotics (SAR) is a comparatively new field of robotics that focuses on developing robots capable of assisting users through *social* rather than *physical* interaction. Just as a good coach or teacher can provide motivation, guidance, and support without making physical contact with a student, socially assistive robots attempt to provide the appropriate emotional, cognitive, and social cues to encourage development, learning, or therapy for an individual. SAR focuses on the challenges of providing motivation, coaching, training, and rehabilitation through nonphysical interaction; such systems have been validated in hands-off stroke rehabilitation, social skill training of children with autism, and eldercare, among others. In contrast, most of rehabilitation robotics focuses on physical interaction with the patient; such systems have been validated in hands-on stroke rehabilitation. Social robotics (Chap. 72) focuses on endowing robots with the ability to behave in socially aware and engaging ways; such systems have been validated

in museums, movies, classrooms, and informal settings. Service robotics can be seen as the overarching field that encompasses much of the work above.

A socially assistive robot is a system that employs hands-off interaction strategies, including the use of speech, facial expressions, and communicative gestures, to provide assistance in accordance with a particular assistive context. SAR systems equipped with motivational, social, pedagogical, and therapeutic capabilities have the potential to improve access to personalized care, training and rehabilitation to large populations, including individuals post-stroke, elderly, and children with social and developmental disabilities, in order to enhance their quality of life. An effective socially assistive robot must understand and interact with its environment, exhibit social behaviour, focus its attention and communication on the user, sustain engagement with the user, and achieve specific assistive goals. The robot must do all of this in a way that is safe, ethical and effective for the potentially vulnerable user. Socially assistive robots have been shown to have promise as therapeutic tool for children, the elderly, stroke patients, and other special-needs populations requiring personalized care.

73.2 The Need for Socially Assistive Robotics

The need for socially assistive robots is driven not only by rapidly growing populations that need additional assistance (including the elderly, individuals with cognitive disabilities, and individuals who require non-physical support during rehabilitation) but also by the recognition that social robots can have a substantial positive impact on personal challenges such as maintaining a healthy diet, supporting an active lifestyle, maintaining therapeutic programs, and supporting individualized education [73.1].

One of the most rapidly expanding populations requiring daily assistance is the elderly. The United Nations estimates that the population of those aged 60 and older will double in the next thirty years, with the elderly outnumbering children for the first time in history by 2045 [73.2]. Space and staff shortages at nursing homes and other care facilities are already an issue today. As the elderly population continues to grow, a great deal of attention and research will be dedicated to assistive systems aimed at promoting ageing-in-place, facilitating living independently in one's own home as long as possible. While many of these users will require some degree of physical assistance (such as standing up or carrying heavy groceries), many more are expected to require social and cognitive support to reduce isolation,

maintain active and healthy lifestyles, and to assist in daily therapy routines.

Individuals with cognitive disabilities and developmental and social disorders constitute another key growing population that can benefit from SAR in the contexts of special education, therapy, and training. Autism spectrum disorders (ASDs) have been the focus of much of the research in this area due to their prevalence, rapid growth of diagnoses, inherently social nature, and the critical need for long term, intensive treatment. Current research suggests that 1 in every 60 children in the United States will be diagnosed with ASD; the rate of diagnosis has increased sixfold between 1994 and 2003 [73.3]. The cause of the increase is not yet known. However, early intervention is critical to a positive long-term outcome, and many individuals need high levels of support and care throughout their lives [73.4–8]. Research into applying robots as therapy tools for ASD has focused on how to support repetitive, but necessary, social and behavioral therapies [73.9].

Motivation is recognized as the most significant challenge in physical rehabilitation and training [73.10]. SAR technology has the potential to provide novel means for monitoring, motivating, and

coaching. Post-stroke rehabilitation is one of the largest potential application domains, since stroke is a dominant cause of severe disability in the growing ageing population. In the United States alone, over 700 000 people suffer a new stroke each year, with the majority sustaining some permanent loss of movement [73.11]. Stroke patients frequently have difficulty with everyday functional movements and activities; the loss of function can be decreased through rehabilitation therapy during the critical post-stroke period. Such rehabilitation therapy involves carefully designed repetitive exercises, which can be passive and active. In passive exercises, the therapist (or a robot) actively helps the patient to repeatedly move the stroke-affected limb as prescribed. In active exercises, the patient does the work him/herself, with no physical assistance.

Finally, there is growing interest in using socially assistive robots to support an active and healthy lifestyle. These applications are again motivated by rapidly growing prevalence of obesity and a lack of effective interventions that are not labor-intensive. Childhood and adolescent obesity has been related to a host of adverse

proximal and distal health outcomes, including high cholesterol and triglycerides, hypertension [73.12], insulin resistance [73.13], type 2 diabetes [73.14], nonalcoholic fatty liver disease [73.15], as well as breast, colorectal, and other cancers [73.16]. Furthermore, childhood obesity sustains adverse consequences over the entire life span. In one review, all of the 25 longitudinal studies surveyed showed that overweight and obese youth were at higher risk of becoming overweight adults [73.17]. Per capita medical spending for an obese person is roughly 42% higher than for a person of normal weight [73.18] and outranks the health costs of both smoking and drinking alcohol [73.19]. Understanding, preventing, and treating childhood obesity is therefore a top public health priority [73.20]. Education about health impacts of obesity in addition to coaching and motivation for a healthy lifestyle are known to be effective means of lowering obesity rates [73.21]. SAR has the potential to play an important role in this context as an affordable and accessible means of providing personalized coaching, motivation, and training for exercise and healthy eating habits [73.22].

73.3 Advantages of Embodied Robots over Virtual Agents

Compared to virtual agents, robotic agents are typically more expensive, more difficult to replicate and distribute, more difficult to maintain and support, require a longer development time, and more fragile and susceptible to damage and system failure. In physically assistive tasks, virtual agent alternatives are not possible; manipulation of physical objects requires a physical presence. For socially assistive tasks, the added costs of a physical robot must be justified in comparison with a virtual agent solution.

73.3.1 Embodiment and Social Influence

One primary reason for using a physical robot in a socially assistive task is that robots can often exert more social influence over the user compared to a virtual agent. Socially assistive tasks often require the user to engage in tasks (such as therapy or homework) that are challenging and that the user might need encouragement or guidance to maintain. Multiple studies have demonstrated that physically embodied and collocated robots are more capable of generating the social presence to convince users to take these challenging steps. A physically present robot yields significantly more compliance to its requests, even when those requests are unexpected or unconventional, than a video representation of the same robot [73.23]. Kidd and

Breazeal [73.24] developed a table-top robot to serve as a daily weight-loss advisor; it engaged users through a touch-screen interface, tracked user progress and the state of the user-robot relationship over time, and was tested in a six-week field study with participants at home. The study compared the robot interactions against alternative weight loss methods, including using a standalone computer and maintaining paper logs, and found that participants exercised and tracked their caloric intake for nearly twice as long when interacting with the robot than with the other methods.

Interactions with physical robots are also more engaging and credible than virtual agents in cooperative task scenarios. For example, following a cooperative block-stacking task with a talking agent, participants found an agent more engaging, enjoyable, informative, and credible if it were a physically embodied robot, than if it were a virtually embodied animated character [73.24]. Other work has shown that after playing a cooperative game, people most enjoyed, and attributed the most watchfulness and helpfulness to a physically embodied robot than to a virtual embodiment (a graphical simulation) of the same robot [73.26]. Bartneck [73.27] conducted a study comparing the effectiveness of an emotionally expressive robot, eMu, with its screen character version in engaging users in a simple negotiation task, and found that participants

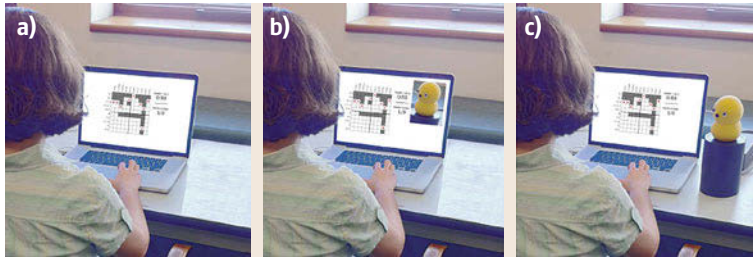


Fig.73.1a–c The physical presence of a robot tutor (c) has been shown to increase learning gains during a puzzle solving task substantially more than when the same tutoring lessons are delivered by a video of the same robot (b) or from a disembodied voice (a) (after [73.25])

exerted more effort and received higher task scores when interacting with the physical eMuu than with the simulated eMuu. *Jung and Lee* [73.28] also demonstrated the positive effects of physical embodiment in relation to interactions with both a Sony Aibo robot and an anthropomorphic dancing robot, April. Another study compared a physical co-present robot, to a remotely located one shown on the video screen, to a simulation of the same robot, all in the same interaction context; the study participants rated the co-present robot as more helpful, watchful, and appealing than remote and simulated counterparts [73.29]. These findings suggest that physical embodiment affords greater social attribution or enjoyment of an agent, than does virtual embodiment.

73.3.2 Embodiment and Learning

Physical robots have also been shown to enhance learning and impact later behavioral choice more substantially than virtual agents. *Leyzberg et al.* [73.25] showed that even when delivering the same lessons on solving cognitive puzzles, users improved their performance during a 20 min session almost twice as much when those lessons were delivered by a physical robot rather than by an on-screen video of the same robot. *Kiesler et al.* [73.30] used task performance measures to find that participants who received health advice from a physically present robot were more likely to choose a healthy snack than participants who received the same information in robot-video or on-screen agent conditions. *Kidd and Breazeal* [73.22] demonstrated that users were more likely to continue sessions with a robot weight-loss coach than with a virtual coach over a period of six weeks (Fig. 73.1).

73.3.3 Embodiment and Special Populations

While most of the investigations of the impact of physical embodiment on socially assistive tasks have been conducted with typical adults, embodiment effects have also been demonstrated on many of the particular populations that SAR projects typically target. *Tapus* and

Matarić [73.31] found that individuals suffering from cognitive impairment and/or Alzheimer's disease reported being more engaged with a robot treatment than a similar on-screen agent treatment. Numerous studies have demonstrated that children and adolescents with ASD engage readily with robots even when those children are unlikely to engage with animated characters on a screen [73.9, 32].

This impact of embodiment on preschool-age children has been of particular interest to educators and developmental psychologists. Although preschoolers learn from watching television and on-screen agents, many studies have focused on how learning and behavior shaping are more robust and generalize more readily when embedded in real time interactions with a physical agent:

1. Preschool children are multimodal learners, learning and retaining information better if there are overlapping modalities of experience [73.33–35].
2. Infants and preschool children off-load cognitive functions to the 3-D (three-dimensional) spatial structure of the world, for example, remembering the direction of attention rather than the content and then looking back to a location to re-perceive the content [73.36–38].
3. Children learn by physically manipulating and grouping objects [73.39, 40].
4. Preschool children learn from gross (whole body) movements; they do not have the fine motor skills to work in a limited spatial arena (such as a computer screen) and do not sustain attention when their gross motor activity is limited [73.41].

These facts suggest that learning and development will be best achieved in physical environments with physically realized teachers. Robotics may offer a mechanism to augment and support teacher–child and parent–child interactions.

Embodiment studies that have targeted the elderly population include the work of *Heerink et al.* [73.42], who investigated the acceptance of assistive social agents by older adults. The robot used in their evaluation was a table-top robot (the iCat), and was either controlled via a human operator during interaction with

elderly users (Wizard of Oz study), or interacted with users through a touch–screen interface. The interactions consisted primarily of short informational or utility interactions (e.g., medication/agenda reminders, weather forecast, companionship). *Fasola and Matarić* [73.43] also investigated the role of embodiment in a **SAR** exercise coach system, with a between-subjects study with participants split into two groups: physical robot coach versus virtual robot coach. Participants engaged in four exercise sessions over a two-week period, with each session lasting 20 min. The results of the between-subjects data analysis showed participants rated the physical robot significantly more positively than the virtual robot across all of the subjective measures, including enjoyableness and usefulness of the interaction, and also in terms of helpfulness, intelligence, social presence, and companionship of the robot coach. Direct comparison among the conditions also favored the physical robot significantly.

73.3.4 Evaluation of **SAR** Systems

One of the unique features of **SAR** is its evaluation process. All robotics requires the implementation of a physical system and its evaluation in the physical world, ideally outside of the laboratory setting, as close

to the intended final use as possible. In reality, however, the majority of research robots are evaluated in laboratory settings, because the alternative is prohibitive due to cost or access or both.

HRI puts the human in the loop and therefore requires evaluation with human users. Since human behavior is complex, it is not readily simulated. Consequently, **SAR**, which involves **HRI**, also requires evaluation with human users. However, to provide truly relevant and realistic evaluation for **SAR** systems, such systems must be tested with the intended populations, since testing with healthy adults is not appropriate for systems aimed at stroke patients, testing with adults is not appropriate for systems aimed at children, and so on.

Consequently, for a **SAR** approach to be truly evaluated, it needs to be tested with members of the intended end-user population, the more rigorously the better, according to the principles and best practices of human subject evaluations, as well as consistent with all the ethical rules associated with such procedures (Sect. 73.11). As a result, **SAR** development and evaluation can be time-consuming and requires multidisciplinary expertise that goes beyond robotics into social science and, as relevant, health science or education, among other disciplines.

73.4 Motivation, Autonomy, and Companionship

SAR systems equipped with motivational, social, and therapeutic capabilities have the potential to enhance user skills and quality of life. Motivation is a fundamental tool in establishing adherence to a training, rehabilitation, or therapy regimen and in promoting behavior change; therefore methods aimed at improving motivation are likely to be useful in the **SAR** contexts. There are two forms of motivation: intrinsic motivation, which comes from within a person, and extrinsic motivation, which comes from sources external to a person. Intrinsically motivated activities are those characterized by enjoyment [73.44]. Extrinsic motivation, though effective for short-term task compliance, has been shown to be less effective than intrinsic motivation for long-term task compliance and behavior change [73.45]. Intrinsic motivation, however, can be and often is affected by external factors, thereby offering a promising avenue for future **SAR** research. In a task scenario, for example, the instructor (or a socially assistive robot) can impact the user's intrinsic motivation through verbal feedback. Praise is considered a form of positive feedback and has the potential to increase the user's intrinsic motivation for performing the task, while criticism, a form of negative feedback, tends to negatively

impact the user's intrinsic motivation [73.46, 47]. The effect of positive feedback is closely tied to the user's own perceived competence at the task; once the user believes he is competent at the task, then additional praise no longer affects his intrinsic motivation.

Verbal feedback provided to the user by the instructor plays an important role in task-based motivation, but the task itself and how it is presented perhaps plays an even more significant role. *Csikszentmihalyi's* research suggests that [73.44]:

when one engages in an optimally challenging activity with respect to one's capacities there is a maximal probability for task-involved enjoyment or flow.

Therefore, an instructor that oversees user performance in a task scenario should also be aware of the user's current affective state or try to infer that state from task performance. The task must be continually adjusted to meet the appropriate needs of the user in order to increase or maintain intrinsic motivation to perform the task.

Another task characteristic with the potential to influence user enjoyment is the incorporation of direct

user input. Studies have shown that tasks that support user autonomy and self-determination lead to increased intrinsic motivation, self-esteem, creativity, and other related variables among the participants [73.48], all of which are essential for achieving task adherence and long term behavior change. Self-determination represented in the task such as choice of activity [73.49],

choice of difficulty level [73.50], and choice of rewards [73.51] have been shown to increase or be less detrimental to intrinsic motivation when compared to similar task conditions that do not involve choice. The positive impact of self-determination in task scenarios has also been supported by studies investigating behavior change [73.52, 53].

73.5 Influence and the Dynamics of Assistive Interaction

While social robotics has approached the issues of modeling the dynamic interplay of social interactions (Chap. 69), assistive interactions are unique among these social engagements as they must simultaneously support the needs of the engagement itself (by maintaining interest, novelty, and the conventions of social behavior) as well as guide the interaction toward the long-term behavioral or educational goals of the system. These two goals can often be in conflict; at times a good teacher (or coach, or socially assistive robot) must sacrifice some of the enjoyment of the interaction, or bend a social rule, in order to promote an educational goal. *Huang and Mutlu* [73.54] recently found some evidence that a robot could make some of these tradeoffs by changing its nonverbal behavior, focusing either on improving task performance (recall in a storytelling task) or on improving social engagement by varying the type of gaze behavior used by the robot.

Because the socially assistive robot must take an active part in shaping this interaction toward particular goals, the nature of the representations and the way in which this influence can be applied to shape the dynamics of the assistive interaction represents a core research question for SAR. Researchers address questions such as:

- What abstractions allow a robot to model the unique dynamics of a social interaction with a user in order to shape the user’s behavior?
- Can we define a set of computational primitives that describe social roles, concepts, or properties in such interactions?
- Can this primitive set provide a basis of representations that allows robots to capture in real time the nuances of interaction, to shape and have their behavior shaped by that interaction, while allowing

generalization and comparisons across users, time scales, and contexts?

Much of the research in this area is based upon foundational psychological properties of human–human social interaction including agency, intentionality, causality, social roles, and goal attribution. These foundational elements discriminate between agents and objects, delineate which elements of the world can move with goal-directed purpose, and provide the primitive structure for describing cause and effect. If we are to build socially assistive robots, these systems must see the world in the same way that we humans do, in the same categories of animate and inanimate, and attribute cause and blame in the same way that we do.

Current computational models represent these features explicitly, with users overtly detailing their goals and intentions in an operationalized way [73.55]. In contrast, people are able to detect and analyze each other’s agency and intentions *on line*, in a way that is often implicit, automatic, effortless, and even irresistible. To be successful, a socially assistive robot must understand, model, and engage in the dynamics of social interaction, so that computational systems can detect, analyze, and manipulate agency, intention, and other social primitives in dynamic environments in a way that is akin to how people do the same for social perception and behavior. These models must operate over a wide range of time scales and across input modalities (visual, auditory, tactile, etc.) and must be capable of interpreting and responding to social overtures in real time and with only minimal latency. Multiple studies have examined particular foundational aspects of the dynamics of interaction [73.56–58] as well as how persuasion might occur within those dynamics [73.59], but a complete model of the dynamics of social interaction remains one of the key research areas addressed within SAR.

73.6 Personalization and Adaptation to Specific Needs and Abilities

A second core research area for SAR concerns the personalization of the robot to the ever changing needs

and abilities of the user. While existing studies in social robotics often focus on a single matching process

by which the behavior of the robot is changed to optimize the properties of the interaction at a single moment in time, adaptation and personalization in assistive tasks should ideally treat the goal as an ever-changing target. As the assistive interaction is often sustained over substantially longer periods of time than other social robot interactions (lasting perhaps months or years), SAR systems should assume that the preferences, needs, and capabilities of the user change over the course of the interaction. Research in this area focuses on questions such as: How can we design a robot that adapts to each user's individual social, physical, and cognitive differences? How can a robot utilize patterns of interactions observed with other users (and possibly other robots) to bootstrap its own attempts at interaction? How do novelty and continuing personalization in interaction create and support trust, learning, and adaptation for improved outcomes for its user?

Socially assistive robots could greatly benefit from adapting to each individual user's unique social, cognitive, and physical abilities. Computationally, the challenge in constructing such a system stems from the individual differences among users and adaptation must occur at multiple levels of abstraction and time scales. At a given moment, robot responses that one user might find frustrating might be optimally engaging to another,

or even to the same user under different conditions or at different times. Their responses should also change over time as the user becomes tired, frustrated, or bored. Responses must also vary from session to session or day to day so that interactions remain engaging and interesting.

Very little research to date addresses learning through personalized social interaction [73.60], especially with populations like children, the elderly, or individuals with social and cognitive deficits. Various learning approaches for HRI have been proposed [73.61], but to date, none have included the user's profile, preferences, and/or personality. The robot's capability to adapt to an individual user's needs and abilities must be bounded by the social and cultural context and while filling the role of a supportive partner or peer. The majority of current machine learning methods are focused on learning specific policies or parameters for tasks or behaviors. While there is a plethora of available learning methods, and some are particularly relevant to SAR, such as user state and activity modeling [73.62, 63], learning by imitation and from demonstration [73.64–68], and learning interaction models from crowd-sourced interaction [73.69], no work to date has focused on adapting to individual differences.

73.7 Creating Long-Term Engagement and Behaviour Change

The ultimate objective for any socially assistive robot is to alter the long-term behavior of the user in line with the behavioral, therapeutic, or educational goals that the robot was designed to support. For many of the application domains covered by SAR systems, this change might require months or years of interaction. A critical research issue for SAR is the development of systems that can maintain these long-term social interactions, monitor the behavioral changes of the user over these long-term interactions, and promote activities that support selective changes in behavior.

Research questions related to this area include: How can a robot continue to be interesting and engaging to a user over an extended time period? What social behaviors and attributes are needed to establish and sustain trust, rapport, and comfort with the user over time to build a successful relationship that continues to provide value? How can a robot continue to adapt to and autonomously guide its user through successive milestones in order to achieve desired learning or behavior change outcomes over longitudinal time scales? What strategy should a robot employ to motivate and maintain lessons or activities, and how should this strategy evolve over time? How can the robot recognize when

its goals related to the behavior change of the user have been achieved, or when intermediary goals have been achieved?

To better fill the social role of supportive partners, socially assistive robots should adapt their behavior and actively planning the trajectory of interactions to guide users toward learning or behavioral goals. The ability to adapt and plan should be demonstrated at multiple time-scales and abstraction levels so as to enable long-term engagement over days, weeks, months, and eventually years. Such capability is particularly important for special populations who may have different responses to techniques and methods that are often employed with typical adults. Almost no work to date has focused on the computational challenges involved in creating social interactions that persist over multiple weeks, months, or years. Early efforts in the area of life-long learning still operate on short time-scales (e.g., two or three cases/tasks) compared to the weeks and months that will be necessary for SAR systems. This particular goal presents a myriad of interesting and challenging applications of complex computational methods such as machine learning. Socially assistive robots capable of long-term adaptation must constantly

sample new interaction and teaching strategies while exploiting previously learned preferences of each individual user and between users, all in an online setting. Extending engagement, social support, and guidance to long-term interaction requires more than scaling

up existing methods and measures. A major scientific goal for SAR research is to develop new insights that enable long-term adaptive support and guidance to the user in order to sustain a productive assistive relationship.

73.8 SAR for Autism Spectrum Disorder (ASD) Therapy

Some of the earliest and most extensive investigations of SAR have focused on the diagnosis and treatment of autism spectrum disorders. Driven by pressing needs from a rapidly expanding population and remarkable early results, a diverse set of robotics research groups have examined the responses of individuals with autism spectrum disorders to robots [73.9, 32].

73.8.1 Summary of ASD-Related Challenges

Autism is a pervasive developmental disorder marked by severe deficits in social functioning such as difficulties recognizing body language, making eye contact, and understanding the emotions of other people [73.4]. It is typically associated with a range of cognitive and attentional deficits [73.70, 71] as well as tendency to engage in preservative and self-stimulatory behaviors. Expression of particular behaviors is highly heterogeneous and associated with notable intra-individual variation in the level of functioning in specific domains. That is, while some children have exceptional cognitive skills, others struggle with major challenges in these areas.

ASD has received a heightened interest from researchers in recent years due to, in part, an unprecedented increase in the incidence rate. ASD is estimated to affect one in every 60 children in the United States, a rate that is roughly eight times higher than the best estimates from 20 years ago [73.72]. ASD is a behaviorally specified disorder [73.5]; there is no blood test, no genetic screening, and no functional imaging test that can diagnose ASD. Diagnosis relies on the clinician's intuitive feel for the child's social skills including eye-to-eye gaze, facial expression, body postures, and gestures. These observational judgments are then quantified according to standardized protocols [73.6, 7, 73, 74] that are both imprecise and subjective. The broad disagreement of clinicians on individual diagnoses creates difficulties both for selecting appropriate treatment for individuals and for reporting the results of population-based studies [73.8, 75].

ASD is a lifelong disorder; there is no known cure. However, early, sustained, and intensive intervention

using a variety of behavioral techniques have been demonstrated to produce substantive gains in many individuals with ASD [73.5]. These therapeutic approaches often focus on traditional behavioral therapies in which a skilled therapist guides an individual with ASD through a series of repetitive exercises aimed at improving daily living and/or functional social skills. These techniques require a tremendous amount of labor, and attempts to use technological innovations to alleviate some of this burden have been a popular research topic. For example, pet-assisted therapy [73.76, 77], computer-assisted therapy [73.78–80] and virtual reality-based approaches [73.81, 82] have all been studied. While these have shown some success, there has been limited investigation of the parameters of the conditions necessary to generalize the benefits to interactions with human partners. Among nonhuman partners, robots that provide instruction, support, and assistance through social interaction have been seen as a potential mechanism for supporting therapy and daily living for individuals with ASD [73.1, 83].

Robots promise unique practical advantages over other nonhuman interactive partners. First, they can potentially provide identical delivery of stimuli, establishing a uniquely high level of control in diagnosis and assessment [73.83]. Second, they do not require the months or years of training that animal assistants may need, as robots can be designed to allow flexible customization. Third, they offer a potential for tactile interface and the immediacy of embodied agency, which computer programs and virtual realities cannot provide. In cases in which human or animal therapeutic aids may be unavailable or are prohibitively expensive, and where software or virtual reality therapeutic tools cannot provide sufficient embodiment, robots may provide an especially useful addition to therapy.

73.8.2 User Study Insights

Research in this area has shown exciting, but often preliminary, benefits to individuals with ASD, including increased engagement in tasks, increased levels of attention, and novel social behaviors such as joint attention and spontaneous imitation, when robots are part of

the interaction [73.83–89]. Much of the early work in this domain was exploratory, performed on small sample sizes (typically fewer than 5 individuals), lacked quantitative measurements of success, failed to include a control group, and had minimal diagnostic and inclusionary criteria. Given the heterogeneity of ASD, these exploratory studies were frequently dismissed by the clinical research community. These exploratory studies however were instrumental in laying the groundwork for the more extensive and detailed studies that are being performed today [73.9].

More recent studies have focused on how robots can enhance human-to-human social behavior in children with ASD and have included statistically valid sample sizes, carefully designed control conditions, and extensive diagnostics to accurately describe the population being studied. For example, *Kim et al.* [73.90] recently demonstrated a robot that engaged children in a vocal prosody training task. Children with ASD were more likely to use appropriate inflection in their voices when engaging the robot than when interacting with a familiar clinician. Furthermore, some children in this study demonstrated increased frequency of social gaze behaviors to an adult (including social referencing) immediately following interaction with a social robot. *Feil-Seifer and Matarić* [73.91] recently demonstrated that children with ASD demonstrated an increased social response to a robot that was socially responsive than to one that was not. The study included a comparable toy as a control and its results included novel insights about child–robot interactions for verbal and nonverbal children with ASD (Fig. 73.2,73.3).

73.8.3 Research Directions

While these *HRI* studies offer the hope of a novel therapeutic approach, they have to date neither explained why robots provoke these responses in children nor demonstrated that a long-term behavioral change in children can be generated that generalizes to human–human interactions. A number of possible hypotheses could explain the increase in social behavior observed

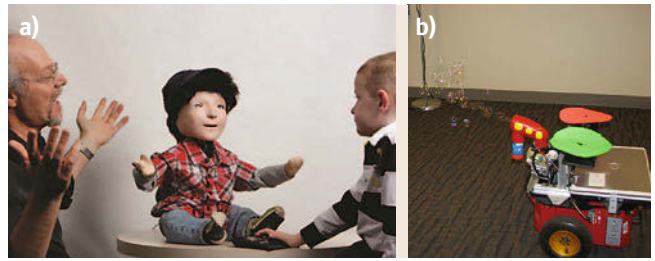


Fig.73.2a,b Both highly anthropomorphic robots ((a) Kaspar from the University of Hertfordshire) and highly mechanistic robots ((b) Bubblebot from the University of Southern California) have shown increased social responses of children with ASD during interactions with robots

during and after interactions between an individual with ASD and a robot. Perhaps robots offer a more predictable interaction, or a more selective and simplified set of social cues to be interpreted, or are more overt in their behavioral responses and easier to engage in reciprocal interactions. There is anecdotal evidence that some of these may not be a satisfactory explanation [73.83,90], but a robust explanation of why these effects are so notable in interactions with individuals with ASD has yet to be described.

Constructing autonomous systems is particularly challenging for this population. The diversity of abilities and deficits within the ASD population results in vast differences in the rate of interaction, the mode of interaction (e.g., verbal versus nonverbal), the social skills to be included in the training, and even the criteria for what constitutes a successful application of a social skill [73.32]. While a few studies [73.92] have begun to incorporate completely autonomous systems, most are still utilizing wizard-of-Oz techniques to deal with the variations across users.

Perhaps the most clinically important research direction is to establish that *HRIs* provide a long-term, measurable change in human–human interactions. Nearly all of the studies carried out to date (with the exception of [73.87]), focus on a small number of short interactions (typically spanning a combined time of less



Fig.73.3a–c *Kim et al.* [73.89,90] demonstrated increases in child–adult interactions following a short (5 min) interaction with a robot. These images come from video captured before (a), during (b), and after (c) an interaction with a Pleo robot, which focused on prosodic production

than an hour). As behavioral change even with an expert clinician can require hundreds of hours of training, our research studies must extend to more lasting interactions that span weeks and months. Furthermore, most studies to date focus on the development of social behaviors directed at the robot. These robot-directed behaviors have minimal clinical value unless they can be shown to generalize to human–human interactions.

(One exception is the studies by *Kim et al.* [73.89, 90] which demonstrated that children with ASD show a significant improvement in face-to-face interactions with an adult immediately following an interaction with a robot tutor). To provide therapeutic value to an individual with ASD, interactive robots must provide either a measurable benefit to their ability to engage with other people.

73.9 SAR Supporting Rehabilitation

SAR is especially well suited for use in the process of rehabilitation, which involves regaining function lost due to illness or trauma. Where rehabilitation robotics focuses on hands-on **HRI**, in contrast, **SAR** focuses on providing motivation and coaching in order to facilitate the rehabilitation process. Since motivation has long been recognized as a major factor in rehabilitation, **SAR** has the potential to play a key role in this health context. **SAR** systems for supporting rehabilitation have been developed and tested with stroke patients [73.93, 94] and Alzheimer’s patients [73.95], and are being considered for use in traumatic brain injury rehabilitation.

73.9.1 Summary of Rehabilitation Challenges

Stroke is the leading cause of serious, long-term disability in the US and the third leading cause of death [73.96]. In the US alone, over 800 000 people suffer a stroke each year, and nearly 400 000 survive with some form of neurologic disability [73.97]. The number of stroke survivors with disability is expected to double by the year 2025 [73.98]. Over 80% of first-time strokes involve loss of function of the upper limb that significantly impacts the independence and health of the stroke survivor [73.99–101]. The residual disability after stroke is substantial, with over 65% of patients unable to incorporate the affected hand effectively into daily activities. Functional recovery of the arm and hand has generally been resistant to the traditional approaches of stroke rehabilitation compared with that for the lower extremities program [73.99, 102].

Stroke often leaves individuals unable to perform movements with the affected limb even though the limb is not completely paralyzed. This loss of function, termed *learned disuse*, can improve with rehabilitation therapy [73.103, 104]. Clinical studies using motor training have found improvement in functional upper limb performance in patients more than one year post stroke and cortical reorganization and recruitment of adjacent brain areas associated with intensive use of

the affected upper limb have been documented several years after the initial stroke injury [73.105–107]. Repetitive, intense, task-specific practice is effective in rehabilitation [73.108–111]. Indeed, practice is fundamental to motor learning – it is the single most important variable for skill acquisition. However, such practice requires trained coaching and motivation.

73.9.2 Contact Versus SAR (Noncontact) Robotics for Rehabilitation

SAR creates a bridge between rehabilitation robotics, which has historically been contact-based [73.112, 113], with noncontact functionalities, such as companion robotics [73.114, 115]. The noncontact approach defines a key niche for **SAR** that involves an autonomous physically embodied robot providing contact-free monitoring, coaching, and encouragement, while also providing detailed assessments of client progress to key stakeholders including and importantly the user. Unlike rehabilitation robotics, where the application and perception of forces are the main focus, and which are consequently currently limited to in-clinic settings, work with noncontact robots is instead directed at the interaction modalities and motivation strategies for achieving specific goals in the home and community settings.

One of the most important elements of any rehabilitation program is the practice of carefully directed, well-focused and repetitive exercises, which can be passive or active. In passive exercises (also known as hands-on rehabilitation), the patient is helped by a human (or robotic) therapist to appropriately exercise the affected limb(s). In contrast, in active exercises, the patient performs the exercises with no physical assistance. The majority of existing work in rehabilitation robotics focuses on hands-on robotic systems for passive exercise, focusing on attempting to recover upper-limb function primarily through robotic manipulation of the affected-limb. *Burgar et al.* [73.116] developed a robot-assisted arm therapy workstation, in which patients

can exercise their upper limbs and evaluate their performance. A similar device, which also depends on hands-on robotic technology, was developed by *Krebs et al.* [73.117]. Other related systems have been investigated [73.118] and [73.119]. Because human–robot contact involves complex issues of safety, such hands-on robotics methods remain areas of active ongoing research, with many outstanding challenges. Currently, contact rehabilitation robots are not portable; the logistics of contact robot therapy are further limited by cost, availability of adequate amount of practice, expertise necessary to program and execute trials, and liability. Risk of injury to the patient is of concern when movement of a limb with sensorimotor loss is imposed by a robot [73.120, 121]. Finally, intense functional exercise is more likely to sustain the behavior (upper limb functional use) in the long term in contrast to the decline in long-term performance with contact robot systems after therapy has ceased [73.120–122].

The **SAR** system acts as a *coach*, providing encouragement, and direction, and ensuring proper adherence with the therapy regimen. Given the size of the stroke-affected population and the time-intensive personalized requirements, such coaching is not possible with human therapists, creating a niche for technological means of filling the gap. By providing the opportunity for time-extended monitoring and encouragement of rehabilitation exercises in any setting (at the clinic or at home), **SAR** systems complement human care [73.123–126].

73.9.3 User Study Insights

This section reviews some of the insights from **SAR** studies performed with stroke patients. One study [73.93, 127] focused on how different robot behaviors may affect the patient’s willingness to adhere to the rehabilitation program. The study evaluated different voices, movements, and levels of patience on the part of the robot, and correlated those with patient adherence. The robot was equipped with navigation capabilities, so it could find and follow the patient, maneuver itself to an appropriate position for monitoring the patient, and leave when it was not wanted. The robot acquired real-time information about the patient’s use of the stroke-affected limb from inertial measurement unit (**IMU**)-based sensors worn by the patient. Wearable sensors present an important alternative to machine vision, which may not be acceptable to all users due to privacy concerns. The robot used information provided by the wearable sensors to encourage the patient to continue using the limb, or to use the limb more or in a different way, as appropriate. The robot was well received by the patients. Some continued to perform the

activity beyond the end of the experiment, providing further evidence of improved adherence well beyond any novelty effects. As expected, there were significant personality differences among the patients; some were highly adherent but appeared un-engaged by the robot, while others were highly engaged and even entertained, but preferred to interact with the robot rather than perform the coached exercises. This leads toward interesting research questions of how to define adaptive robot-assisted rehabilitation protocols that will serve the diverse user population as well as the time-extended and evolving needs of every individual user.

Modeling personality in order to customize **HRI** has a particular relevance to stroke rehabilitation because pre-stroke personality has a great influence on post-stroke recovery [73.96]; individuals classified as extroverted before the stroke mobilize their strength more easily to recover than do introverted subjects [73.128]. Further, work in human–computer interaction (**HCI**) has demonstrated the similarity-attraction principle, which posits that individuals are more attracted to others manifesting the same personality as theirs [73.129–131]. *Tapus* and *Mataric* [73.132] performed a **SAR** study to test related effects. In a series of experiments with a simple mobile robot equipped with a camera and a microphone, participants were asked to perform four tasks (designed as functional activities) similar to those used during standard stroke rehabilitation. The participants completed a personality assessment questionnaire before the experiment; the resulting personality based specifically on the extroversion–introversion dimension was used to determine the robot’s personality. The behavior control architecture was based on the model of reciprocal influences on behavior [73.133]. The robot expressed its personality through several means: (1) proxemics (social use of space; extroverted personalities used smaller personal distances) [73.134]; (2) speed and amount of movement (extroverted personalities moved more and faster); and (3) verbal content (extroverted personalities talked more assertively (*You have done only x movements, I’m sure you can do more!*), using a challenge-based style compared to a nurture-based style (*I know it’s hard, but remember it’s for your own good.*)). The experiment compared personality-matched versus personality-mismatched (random) conditions. The results showed that the robot’s personality was fundamental to the quality of the interaction. Two statistically significant results were found: (1) participants consistently performed better on the task when interacting with the personality-matched robot; (2) participants reported preferring the personality-matched robot. *Tapus et al.* [73.94] then expanded on this work by enabling the **SAR** system to adapt its personality based on the past interactions with the user.

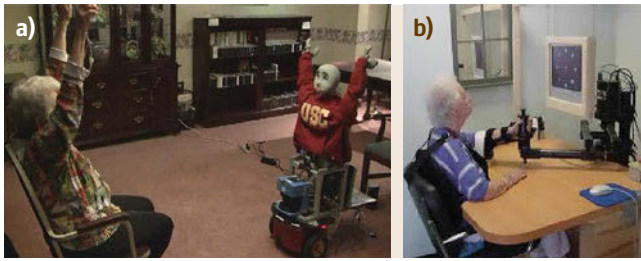


Fig.73.4a,b Seated exercise coaching with a socially assistive humanoid robot on wheels, (a) Bandit, from the University of Southern California, and (b) upper extremity rehabilitation manipulandum

Formulated as policy gradient reinforcement learning (PGRL), the adaptation allowed for optimizing the interaction parameters: interaction distance/proxemics, speed, and verbal content (what the robot says and how it says it). The learning algorithm was initialized with parameter values that were in the vicinity of what was thought to be acceptable for both extroverted and introverted individuals, based on the user–robot personality matching study described earlier. Gradual adaptation around a solution rather than random probing of the solution space is important; if the robot’s initial personality is far off the mark, or if it changes drastically, users are dissatisfied with the interaction. The results provided evidence for the effectiveness of robot behavior adaptation to user personality and performance: users tended to perform more or longer trials under the personality matched and therapy style-matched conditions (nurturing styles were correlated with the introversion, and challenging styles with extroversion).

Another study with stroke patients compared matched humanoid robot and simulated agent implementation of the SAR coach. The study participants were seated at a desk, and were asked by the robot to move magazines from the lower to the higher rack and to de-shelf as many magazines as possible in 6 min. The robot monitored the participant’s motions using a revised version of the motion sensors described above [73.135, 136]. The participants could use the button on a WiiMote to stop the interaction at any time. The IMU data and shelf state (using a scale) were used to classify the movement into states of progress (e.g., resting, picking up magazine, lifting arm, shelving book, lowering arm). In addition to the verbalizations, the robot used *beat gestures* whenever it spoke. This consisted of moving the head, arms, and hands in a beat with amplitude and frequency governed by the characteristics of the phrase that was being uttered. Baseline

movement data were assessed using standard stroke movement tests and task improvement was measured after repeated sessions. The experimental design involved all participants experimenting with both the robot and the computer. Two-thirds of the participants preferred the physical robot, with one third having no preference.

73.9.4 Research Directions

SAR for rehabilitation presents multi-faceted research challenges.

Personalizing the interaction to adapt to the user’s changing state over multiple timescales remains a major challenge, since rehabilitation aims for long-term improvement, but must contend with mood, fatigue, and performance variations within each session, as well as short term trends that may plateau or even reverse. Personalizing the interaction thus requires new ways of integrating robot learning, user modelling, and motivation strategies, among many other SAR research challenges. Creating robotic systems capable of adapting their behavior in order to provide an engaging and motivating customized protocol is a challenging target, especially when working with vulnerable user populations. In the SAR context, behavior adaptation must address both short-term changes that represent individual differences and long-term changes that allow the interaction to continue to be engaging over a period of months and even years. Various learning approaches for HRI have been proposed in the literature [73.61, 65] but this remains a major challenge in robotics in general and in SAR in particular.

Modeling the user and predicting user behavior is a challenge common to HRI and HCI, as well as research in signal processing and related fields. However, SAR also brings up the issue of modelling the identity of the robot character. Specifically, studies in SAR are beginning to show that having not only a personality but also a back story for the robot facilitates user engagement.

Research into relational agents [73.137] has been applied to short-term interactions in medical settings, such as hospital checkout procedures. Some of the insights from that field, including politeness theory, empathy, etc., are being explored in SAR for use in long-term interactions involved in rehabilitation.

Finally, one of the much needed new directions of research is the exploration of bringing together contact and noncontact rehabilitation robotics in relevant domains, in order to enhance the impact of both robotics subfields.

73.10 SAR and Eldercare

73.10.1 Summary of Eldercare Challenges

The growing population of aging adults is increasing the demand for healthcare services worldwide. By the year 2050, the number of people over the age of 85 will increase threefold [73.138], while the shortfall of nurses and caregivers is already an issue [73.139–141]. Regular physical exercise has been shown to be effective at maintaining and improving overall health [73.142–145]. Physical fitness is associated with higher functioning in the executive control processes [73.146] and is correlated with less atrophy of frontal cortex regions [73.147] and with improved reaction times [73.148]. Social interaction, and specifically high perceived interpersonal social support, has also been shown to have a positive impact on general mental and physical wellbeing [73.149], in addition to reducing the likelihood of depression [73.150–153]. Thus, the availability of physical exercise therapy, social interaction, and companionship will be critical for the growing elderly population.

The probability for acquired motor, cognitive, and perceptual disabilities dramatically increases with age [73.154]. Over 50 million Americans have a disability that affects one or more of their major life activities [73.155, 156] and only 30% are employed [73.157]. The economic cost of the associated loss of functioning is high; e.g., the cumulative total of stroke-affected Americans is over 4 million, and the estimated annual burden from stroke-related disability is \$53.6 billion, of which \$20.6 billion is in indirect costs due to lost productivity and income [73.96, 158]. Given projections that the number of people older than 65 years is anticipated to double between 1997 and 2025 [73.156] and that 30% of the population will be over 65 [73.159, 160], we will soon face new major technical and social challenges to attain, prolong, and preserve quality of life.

A especially vulnerable and sizeable population consists of individuals who are aging with disabilities that were acquired at any stage of life, from birth or early in life to stroke or other disorders later in life [73.161]. The number of middle aged and older adults living with disabilities will grow significantly as the U.S. population ages rapidly [73.162]. People who have managed their lives very successfully for years may find that they are experiencing the effects of aging earlier than others or are developing secondary health conditions as they reach their 30s or 40s [73.163, 164]. As persons with disabilities age, progressive declines in health and medical status can challenge the adaptive resources required to maintain functional independence and quality of life [73.165, 166].

Motor and cognitive dysfunctions that accompany chronic illness and disability in late life are major precursors for people who age into disability. Cognitive impairments are associated with increased disability in aging populations [73.167]; 19% of women and 13% of men aged 65–69 live with a disability in mobility [73.168]. The respective percentages increase to 83% and 63% for women and men aged 90–95 [73.168]. These dysfunctions greatly compound the disruptions in overall lifestyle and occupational status experienced by individuals aging with disabilities primarily associated with cognitive or motor deficits. Thus, there is a critical need to develop effective and affordable assistive technologies to improve the motor and cognitive functioning, especially in individuals aging with disabilities. This creates an important niche for SAR.

73.10.2 User Study Insights

The literature that addresses assistive robotics intended for and evaluated by the elderly is limited but growing.

Researchers have investigated the use of robots to help address the social and emotional needs of the elderly, including reducing depression and increasing social interaction with peers. Wada et al. [73.114] studied the psychological effects of a seal robot, Paro, used to engage seniors at a day service center. The study found that Paro, always accompanied by a human handler, was able to consistently improve the moods of elderly participants who spent time petting and engaging with it over the course of a 6-week period. Kidd et al. [73.115] used Paro in another study that found it to be useful as a catalyst for social interaction. They observed that seniors who participated with the robot in a group were more likely to interact socially with each other when the robot was present and powered on, rather than when it was powered off or absent.

Social agents that aim to assist individuals in health-related tasks such as physical exercise have also been developed in the HCI community. Bickmore and Picard [73.137] developed a computer-based virtual relational agent that served as a daily exercise advisor by engaging the user in conversation and providing educational information about walking for exercise, asking about the user's daily activity levels, tracking user progress over time while giving feedback, and engaging the user in relational dialogue.

Fasola and Matarić [73.169] conducted a study to investigate the role of praise and relational discourse (politeness, humor, empathy, etc.) in a SAR exercise

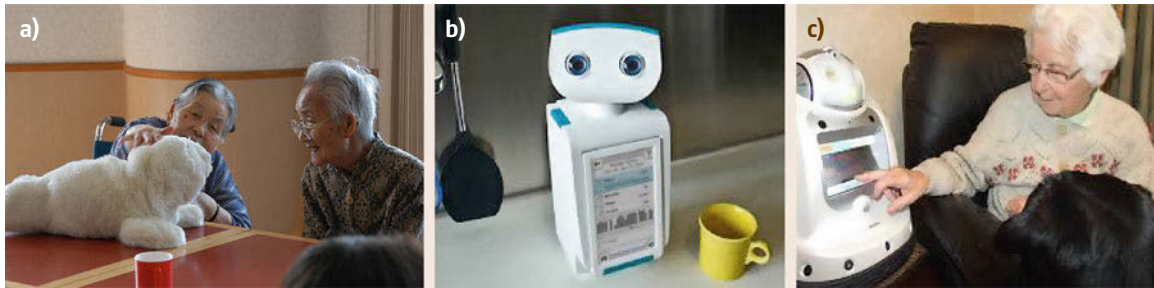


Fig.73.5a–c Paro robot (a) from the University of Tokyo, Autom robot (b) used in an MIT weight-loss study, and Healthbot robot (c) from the University of Auckland used in a large-scale elderly care study

system designed for older adults. The study compared a relational robot versus a nonrelational robot. The relational robot employed praise and relational discourse, while the nonrelational robot guided the exercise interaction without such praise or discourse. Results showed participants rated the relational robot significantly more positively than the nonrelational robot in terms of enjoyableness and usefulness of the interaction, and as a companion and exercise coach. *Fasola and Matarić* [73.169] also conducted a user study to investigate the role of choice and user autonomy within

the same SAR exercise system. The results of the study showed no clear preference for one condition over the other, as the user enjoyment level of the interaction was reported to be equally high for choice and no-choice conditions. This suggests that a hybrid approach that includes both user and robot decision making, personalized and tuned automatically for each user, might ultimately be the best solution for achieving a fluid and enjoyable task interaction for all users. This once again underscores the need for personalized methods of HRI and user modeling and adaptation.

73.11 SAR for Alzheimer's Dementia and Cognitive Rehabilitation

Dementia is a progressive disabling neurological condition that can be a symptom of several diseases, including Alzheimer's, which makes up about half of all cases of dementia. The latest estimate is that 26.6 million people were suffering from Alzheimer's disease worldwide in 2006, and it will rise to 100 million by 2050 – 1 in 85 of the total population [73.170]. More than 40% of those cases will be in late-stage Alzheimer's, requiring a high level of attention equivalent to nursing home care. Individuals suffering from Alzheimer's experience a decrease in verbal and cognitive skills along with the deterioration of strength and flexibility that comes with aging. Rehabilitation therapies for individuals with dementia often focus on both cognitive and motor exercises to in order to preserve patients' autonomy for as long as possible.

Therapy for individuals with dementia must be pervasive and ongoing in their everyday lives. Mental and physical exercise involving art, music, and playing with/tending to animals have been used to preserve cognitive function in older adults who have begun experience symptoms of dementia. However, these therapies can only be offered by well-trained personnel. In particular, animal therapy can involve safety risks for both the animal and the patient. The goal of SAR in this ther-

apy context is to provide a means of providing therapy that is safe, easy to use, and does not require special training.

73.11.1 User Study Insights

In a study by *Tamura et al.* [73.171], an entertainment robot was used as occupational therapy instead of animal-assisted therapy to avoid any danger or injury to the patient and maintain cleanliness. The study compared the effectiveness of a robot animal, AIBO, with a toy. AIBO responded to spoken commands and was demonstrated to severely demented elderly people living in a geriatric home. The most frequent reactions to AIBO consisted of looking at, communicating with, and caring for the robot. The patients recognized that AIBO was a robot but, once the robot was addressed by the experimenters, the patients perceived it as either a dog or a baby. The presentation resulted in positive outcomes for the severe dementia patients, including increased communication between the patients and the robot.

Tapus et al. [73.172] performed a long-term (6-month) study of socially assistive robots in the context of cognitive training for Alzheimer's patients to test if

elderly individuals with Alzheimer's impairments can maintain attention to music with the help of a SAR system. A small group of four participants over 70 years old, suffering from mild to severe cognitive impairment and/or Alzheimer's disease, took part in the study and received pre- and post-study cognitive assessments. Each interacted in one-on-one twice-weekly sessions with the robot, in which the robot presented a music recognition game with three different levels of challenge: difficult (no hints), medium (hints given), and easy (name of song given). The challenge level was adjusted to each participant based on performance. The results obtained over 6 months of robot interaction (excluding the 2 months of learning) suggest that elderly people suffering of dementia and/or Alzheimer's can sustain attention to music across a long period of time and even improve on the music recognition task when coached by a socially assistive robot; the SAR system was able to adapt the challenge level of the game it was presenting to the user in order to encourage task improvement and attention training. Importantly, the participants demonstrated fondness for the robot and included it into their daily narratives (e.g., *My buddy is coming to visit, I don't want to miss it.*).

The multiyear Healthbots project at the University of Auckland is examining the role of telepresence and humanoid robots in assisted living communi-

ties [73.173]. This large study included three different types of robots, ranging from large telepresence to small humanoid, which were deployed as companions and nursing assistants in a retirement village of around 650 residents. Several insights were gained from the long-term deployment, including the preferences of both the elderly users and staff members. The most promising avenue for robotic assistance was a robot that was sent into residents' rooms to remind them to take their medications or fetch them for appointments.

73.11.2 Research Directions

As with all areas of SAR, the user's willingness to engage with a socially assistive robot to accept advice, interact, and ultimately alter behavior depends on the robot's ability to obtain the user's trust and sustain the user's interest. User interfaces and input devices that are easy and intuitive for a range of users, including those with special needs, need to be developed. Social interaction is inherently bidirectional and thus involves both multimodal perception and communication, including verbal and nonverbal means. Toward that end, automated behavior detection and classification as well as activity recognition, including user intent, task-specific attention, and failure recognition, are critical enabling components being developed.

73.12 Ethical and Safety Considerations

SAR, with its focus on developing human-robot relationships and influencing human behavior, naturally brings about several distinct types of ethical considerations.

Safety of the user is the first and most obvious consideration in any area of HRI. Because SAR systems do not involve physical contact initiated by either people or robots, they present a minimum of physical safety issues. However, while physical safety is one of the largest concerns in other areas of robotics research (Chap. 30), in SAR, emotional and other types of non-physical safety must be considered.

As SAR research strives to achieve user engagement and attachment, some critics have argued that such relationships should be reserved for humans only [73.174]. Evaluations of specific SAR systems have triggered ethical dilemmas [73.174, 175]. Turkle [73.174] demonstrated that some participants interacting with robots can correctly identify the robot's intended emotional abilities and operational capabilities. These participants could also correctly distinguish equivalent capabilities in a person, pet, or other relational artifact. However, it

was also demonstrated that some users formed attachments and emotional bonds with robots they were interacting with. These attachments led to misconceptions about the robots' emotional capabilities. For example, one user felt that the robot would miss him when he was gone, something that the robot was not capable of doing. Sharkey and Sharkey [73.175] argue strongly that such attachments in children could lead to malformed development and emotional problems. Some such arguments are based on the notion that human care is replaced by robot care, which is not consistent with the premise of most of SAR research. Most SAR research clearly state that their aim is to *augment rather than replace human care*, as discussed in Sect. 73.7 of this chapter, in the context of SAR for autism spectrum disorders.

Some more pragmatic ethical considerations take into account the inevitable progress of technology, which will render any particular system obsolete well within a user's lifetime, therefore undermining attachment and likely making long-term system operation impossible. Since long-term robot system operation is

a goal of the majority of robotics research, this is not yet a pressing ethical concern, but is one that is well recognized as important.

As one example of ethics applied to SAR in particular, Feil-Seifer and Mataric [73.176] outlines the ethical issues of SAR around the core principles of ethics applied to human subjects, namely beneficence, nonmaleficence, autonomy and justice. The first two principles encompass the SAR issues of relationships, authority and attachment, perception and personifications of the robot, and replacement of hu-

man care/changes to human-human interaction. The third principle, autonomy, spans the issues of privacy, choice, and intentional user deception. Finally, justice spans the complex issues of cost/benefit analysis, and locus of responsibility in the case of failure or harm.

As robots get closer to people, ethical issues become more pressing. It is a good sign that so early in the development of SAR those issues are being actively discussed and considered, toward the development of most ethically informed methods and systems.

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Multimedia Contents



74. Learning from Humans

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This chapter surveys the main approaches developed to date to endow robots with the ability to learn from human guidance. The field is best known as robot programming by demonstration, robot learning from/by demonstration, apprenticeship learning and imitation learning. We start with a brief historical overview of the field. We then summarize the various approaches taken to solve four main questions: when, what, who and when to imitate. We emphasize the importance of choosing well the interface and the channels used to convey the demonstrations, with an eye on interfaces providing force control and force feedback. We then review algorithmic approaches to model skills individually and as a compound and algorithms that combine learning from human guidance with reinforcement learning. We close with a look on the use of language to guide teaching and a list of open issues.

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74.1 Learning of Robots

Robot learning from humans relates to situations in which the robot learns from interacting with a human. This must be contrasted to the vast body of work on robot learning where the robot learns *on its own*, that is, through trial and error and without external guidance. In this chapter, we cover works that combine reinforcement learning (RL) with techniques that use human guidance, e.g., to bootstrap the search in RL. However, we exclude from this survey all works that use purely reinforcement learning, even though one could argue that providing a reward is one form of human guidance. We consider that providing a reward function is akin to providing an objective function and hence refer the reader to the companion chapter on *Machine*

Learning for robotics. We also exclude works where the robot learns implicitly from being in presence of a human, while the human is not actively coaching the robot, as these works are covered in the companion chapter on *Social Robotics*. We hence focus our survey to all works where the human is actively teaching the robot, by providing *demonstrations* of how to perform the task.

Various terminologies have been used to refer to this body of work. These include programming by demonstration (PbD), learning from human demonstration (LfD), *imitation learning*, and *apprenticeship learning*. All of these refer to a general paradigm for enabling robots to autonomously perform new tasks from ob-

serving and learning, therefore, from the observation of humans performing these tasks.

74.1.1 Principle

Rather than requiring users to analytically decompose and manually program a desired behavior, work in **LfD-PbD** takes the view that an appropriate robot controller can be derived from observations of a human's own performance thereof. The aim is for robot capabilities to be more easily extended and adapted to novel situations, even by users without programming ability:

The main principle of robot learning from demonstration is that end-users can teach robots new tasks without programming.

Consider a household robot capable of performing manipulation tasks. One task that an end-user may desire the robot to perform is to prepare a meal, such as preparing an orange juice for breakfast (Fig. 74.1 and  VIDEO 29). Doing so may involve multiple sub-tasks, such as juicing the orange, throwing the rest of the orange in the trash, and pouring the liquid into a cup. Further, every time this meal is prepared, the robot will need to adapt its motion to the fact that the location and type object (cup, juicer) may change.

In a traditional programming scenario, a human programmer would have to code a robot controller that is capable of responding to any situation the robot may face. The overall task may need to be broken down into tens or hundreds of smaller steps, and each one of these steps should be tested for robustness prior to the robot leaving the factory. If and when failures occur in the field, highly-skilled technicians would need to be dispatched to update the system for the new circumstances. Instead, **LfD** allows the end-user to *program* the robot simply by showing it how to perform the task – no coding is required. Then, when failures occur, the end-user only needs to provide more demonstrations, rather than calling for professional help. **LfD** hence seeks to endow robots with the ability to learn what it means to perform a task by generalizing from several observations (Fig. 74.1 and  VIDEO 29).

LfD is not a record and play technique. **LfD** implies learning, henceforth, generalization.

Next, we give a brief historical overview of the way the field evolved over the years. This is followed, in Sect. 74.2, by an introduction to the issues at the core of **LfD**. In Sect. 74.3, we discuss the crucial role that the interface used for **LfD** plays in the success of the teaching, emphasizing how the choice of interface determines the type of information that can be conveyed to the robot. Finally, in Sect. 74.4, we give a generic

view of the main approaches to solving **LfD** and conclude with an outlook on open issues.

74.1.2 Brief History

Robot learning from demonstration started in the 1980s. Then, and still to a large extent now, robots had to be explicitly and tediously hand programmed for each task they had to perform. **PbD** sought to minimize, or even eliminate, this difficult step.

The rationale for moving from purely pre-programmed robots to very flexible user-based interfaces for training the robot to perform a task is threefold. First and foremost, **PbD** is a powerful mechanism for reducing the complexity of search spaces for learning. When observing either good or bad examples, one can reduce the search for a possible solution, by either starting the search from the observed good solution (local optima), or conversely, by eliminating from the search space what is known as a bad solution. Imitation learning is, thus, a powerful tool for enhancing and accelerating learning in both animals and artifacts.

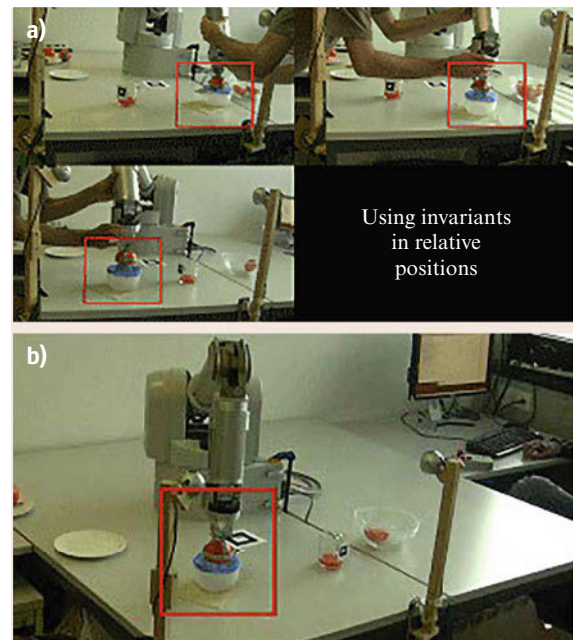


Fig. 74.1 (a) The teacher does several demonstrations of the task of juicing an orange, by changing the location of each item to allow the robot to generalize correctly. That is, the robot should be able to infer, by comparing the demonstrations, that only the relative locations matter, as opposed to the exact locations as recorded from a global coordinate system. (b) The robot can then reproduce the task even when the objects are located in positions not seen in the demonstrations  VIDEO 29

Second, imitation learning offers an implicit means of training a machine, such that explicit and tedious programming of a task by a human user can be minimized or eliminated. Imitation learning is thus a *natural* means of interacting with a machine that would be accessible to lay people.

Third, studying and modeling the coupling of perception and action, which is at the core of imitation learning, helps us to understand the mechanisms by which the self-organization of perception and action could arise during development. The reciprocal interaction of perception and action could explain how competence in motor control can be grounded in the rich structure of perceptual variables, and vice versa, how the processes of perception can develop as means to create successful actions.

PbD promises were thus multiple. On the one hand, one hoped that it would make the learning faster, in contrast to trial-and-error methods trying to learn the skill *tabula rasa*. On the other hand, one expected that being user-friendly, the methods would enhance the application of robots in human daily environments.

At the beginning of the 1980s, LfD, known then as programming by demonstration (PbD), started attracting attention in manufacturing robotics. PbD appeared as a promising route to automate the tedious manual programming of robots, reducing the costs involved in the development and maintenance of robots in the factory.

As a first approach in PbD, symbolic reasoning was commonly adopted in robotics [74.1–5], with processes referred to as *teach-in*, *guiding*, or *play-back* methods. In these works, PbD was performed through manual (teleoperated) control. The position of the end-effector and the forces applied on the object manipulated were stored throughout the demonstrations together with the positions and orientations of the obstacles and of the target. This sensorimotor information was then segmented into discrete subgoals (key points along the trajectory) and into appropriate pre-defined actions to attain these subgoals. Actions were commonly chosen to be simple point-to-point movements that industrial robots employed at this time. Examples of subgoals would be, e.g., the robot's gripper orientation and position in relation to the goal [74.3]. Consequently, the demonstrated task was segmented into a sequence of state-action-state transitions.

To take into account the variability of human motion and the noise inherent to the sensors capturing the movements, it appeared necessary to develop a method that would consolidate all demonstrated movements. For this purpose, the state-action-state sequence was converted into symbolic *if-then* rules, describing the

states and the actions according to symbolic relationships, such as *in contact*, *close-to*, *move-to*, *grasp-object*, *move-above*, etc. Appropriate numerical definitions of these symbols (i.e., when would an object be considered as *close-to* or *far-from*) were given as prior knowledge to the system. A complete demonstration was thus encoded in a graph-based representation, where each state constituted a graph node and each action a directed link between two nodes. Symbolic reasoning could then unify different graphical representations for the same task by merging and deleting nodes [74.2].

Munch et al. [74.6] suggested the use of machine learning (ML) techniques to recognize elementary operators (EOs), thus defining a discrete set of basic motor skills, with industrial robotics applications in mind. In this early work, the authors already established several key issues of PbD in robotics. These include questions such as how to generalize a task, how to reproduce a skill in a completely novel situation, how to evaluate a reproduction attempt, and how to better define the role of the user during learning. Munch et al. [74.6] admitted that generalizing over a sequence of discrete actions was only one part of the problem since the controller of the robot also required the learning of continuous trajectories to control the actuators. They proposed to overcome the missing parts of the learning process by leveraging them to the user, who took an active role in the teaching process.

These early works highlighted the importance of providing a set of examples that are usable by the robot: (1) by constraining the demonstrations to modalities that the robot can understand; and (2) by providing a sufficient number of examples to achieve a desired generality. They noted the importance of providing an adaptive controller to reproduce the task in new situations, that is, how to adjust an already acquired program. The evaluation of a reproduction attempt was also leveraged to the user by letting him/her provide additional examples of the skill in the regions of the learning space that had not been covered yet. In this way, the teacher/expert could control the generalization capabilities of the robot.

With the increasing development of mobile and humanoid robots, the field went on adopting an interdisciplinary approach, taking into account evidence of specific neural mechanisms for visuomotor imitation in primates [74.7–9] and of developmental stages of imitation capacities in children [74.10, 11]. The latter promotes the introduction of socially driven behavior in the robot to sustain interaction and improve teaching [74.12, 13] and of an interactive teaching process, in which the robot takes a more active role and may ask the user for additional sources of information, when

needed [74.14, 15]. Eventually, the notion of *robot programming by demonstration* was replaced by the more biological labeling of *imitation learning*. In essence, a large part of current works in PbD follow a conceptual approach very similar to that followed by these prior works.

Recent progress affected mostly the interfaces at the basis of the teaching. Traditional ways of guiding/teleoperating the robot have been progressively replaced by more user-friendly interfaces, such as vision [74.16, 17], speech command [74.18], data gloves [74.19], the laser range finder [74.20] or kinesthetic teaching (i.e., by manually guiding the robot's arms through the motion) [74.21–23].

The field progressively moved from simply copying the demonstrated movements to generalizing across sets of demonstrations. As machine learning progressed, PbD started incorporating more of those tools to tackle both the perception issue, i.e., how to generalize across

demonstrations, and the production issue, i.e., how to generalize the movement to new situations. Initially, tools such as artificial neural networks (ANNs) [74.24, 25], radial-basis function networks (RBFs) [74.26], and *fuzzy logic* [74.27] were quite popular. These have lately been replaced by hidden Markov models (HMMs) [74.28–33] and various non-linear regression techniques [74.21, 34, 35], as we will discuss in more detail in Sect. 74.4.

New learning challenges were, thus, set forth. Robots were expected to show a high degree of flexibility and versatility both in their learning system and in their control system in order to be able to interact naturally with human users and demonstrate similar skills (e.g., by moving in the same rooms and manipulating the same tools as humans). Robots were more and more expected to act *human-like* to enhance the interaction and so that their behavior would be more predictable and, hence, more acceptable.

74.2 Key Issues When Learning from Human Demonstrations

As mentioned in the beginning, learning from demonstration (LfD) has at core to develop algorithms that are generic in their representation of the skills and in the way they generate the skills.

The field has identified a number of key problems that need to be solved for ensuring such a generic approach to transferring skills across various agents and situations [74.36, 37]. These have been formulated as a set of generic questions, namely *what to imitate*, *how to imitate*, *when to imitate*, and *who to imitate*. These questions were formulated in response to the large body of diverse work in robotics LfD [74.18, 26, 38–41] that could not easily be unified under a small number of coherent operating principles. The above four questions and their solutions aim at being generic in the sense of making no assumptions on the type of skills that may be transmitted.

74.2.1 When and Whom to Imitate

Whom and when to imitate has been largely unexplored so far, and hence to date, only the first two questions have really been addressed. Figure 74.2 and VIDEO 97 illustrate how these two problems can be solved in a principled manner through statistical observation of the demonstrations.

How to Determine the Evaluation Metric

What to imitate relates to the problem of determining which aspects of the demonstration should be imi-

tated. For a given task, certain observable or affectable properties may be irrelevant and safely ignored. For instance, if the demonstrator always approaches a location from the north, is it necessary for the robot to do the same? The answer to this question strongly in-

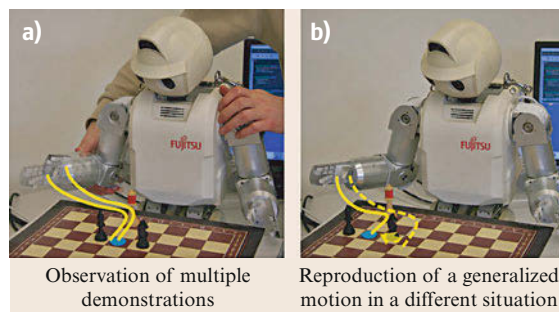


Fig. 74.2 (a) A robot learns how to make a chess move (namely moving the queen forward) by generalizing across different demonstrations of the task performed in slightly different situations (different starting positions of the hand). The robot records the trajectories of its joints and learns to extract invariant features (*what-to-imitate*), i.e., that the task constraints are reduced to a subpart of the motion located in a plane defined by the three chess pieces. (b) The robot reproduces the skill in a new context (for a different initial position of the chess piece) by finding an appropriate controller that satisfies both the task constraints and constraints relative to its body limitation (*how-to-imitate* problem) (after [74.21])

fluences whether or not a derived robot controller is a successful imitation – a robot that approaches from the south is appropriately trained if direction is not important, but needs further education if it is. This issue is related to questions of signal versus noise and is answered by determining the metric by which the resulting behavior is evaluated. Different ways can be taken to address this issue. The simplest approach is to take a statistical perspective and deem as relevant the parts (dimension, region of input space) of the data that are consistently measured across all demonstration instances [74.21]. If the dimension of the data is too high, such an approach may require too many demonstrations to gather enough statistics. An alternative is then to have the teacher help the robot determine what is relevant by pointing out the parts of the task that are most important.

In summary, what to imitate removes consideration of details that, while perceptible/performable, do not matter for the task. It participates in determining the metric by which the reproduction of the robot can be measured. In continuous control tasks, what to imitate relates to the problem of defining automatically the feature space for learning, as well the constraints and the cost function. In discrete control tasks, such as those treated by reinforcement learning and symbolic reasoning, what to imitate relates to the problem of how to define the state and action space and of how to automatically learn the pre/post conditions in an autonomous decision system.

74.2.2 How to Imitate and How to Solve the Correspondence Problem

How to imitate consists in determining how the robot will actually perform the learned behaviors to maximize the metric found when solving the what to imitate problem. Often, a robot cannot act exactly the same way as a human does, due to differences in physical embodiment. For example, if the demonstrator uses a foot to move an object, is it acceptable for a wheeled robot to bump it, or should it use a gripper instead? If the metric does not have appendage-specific terms, it may not matter.

This issue is closely related to that of the correspondence problem [74.36]. Robots and humans, while inhabiting the same space and interacting with the same objects, and perhaps even superficially similar, still perceive and interact with the world in fundamentally different ways. To evaluate the similarity between human behavior and that of robots, we must first deal with the fact that humans and robots may occupy different state spaces, of perhaps different dimensions. We identify two different ways in which states of demonstrator

and imitator can be said to correspond, and give brief examples:

- *Perceptual equivalence*: Due to differences between human and robot sensory capabilities, the same scene may appear to be very different. For instance, while a human may identify humans and

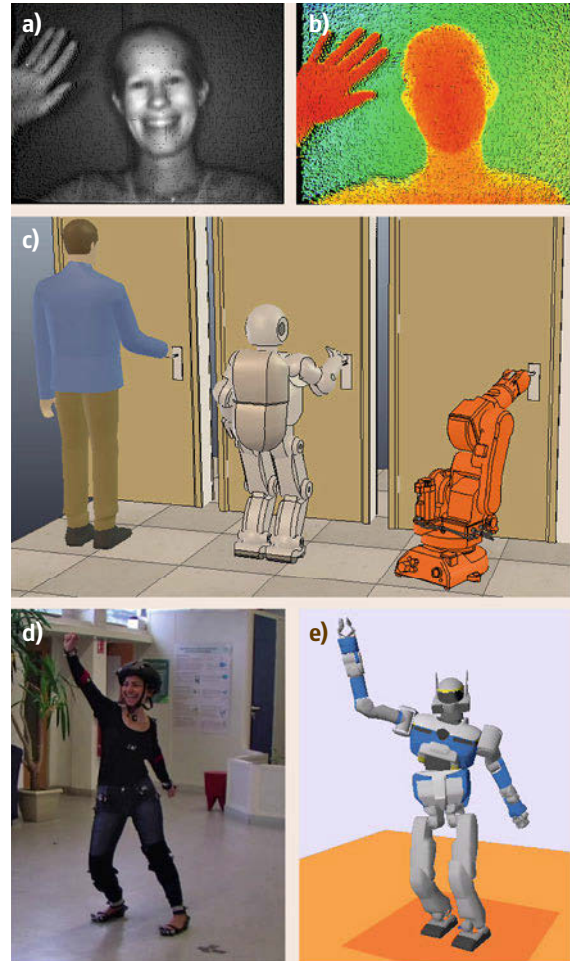


Fig. 74.3 (a,b) Perceptual equivalence (adapted from [74.42]). (c) Physical equivalence. The humanoid robot has the same arrangement of principal articulations as the human demonstrator, but different limb lengths and joint angle limits. The industrial robot has a different number and arrangement of articulations, which makes the mapping problem more challenging (illustration created with the V-REP simulator [74.43]). (d,e) Offline full-body motion transfer by taking into account the kinematic and dynamic disparity between the human and the humanoid [74.44]. See also [VIDEO 98](#) and [VIDEO 99](#) for example of mapping of full body motion from human to humanoids

gestures from color and intensity, a robot may use depth measurements to observe the same scene (Fig. 74.3a). Another point of comparison is tactile sensing. Most tactile sensors allow robots to perceive contact, but do not offer information about temperature, in contrast to the human skin. Moreover, the low resolution of the robots' tactile sensors does not allow robots to discriminate across the variety of existing textures, while human skin does. As the same data may, therefore, not be available to both humans and robots, successfully teaching a robot may require a good understanding of the robot's sensors and their limitations. *LfD* explores the limits of these perceptual equivalences, by building interfaces that either automatically correct or make explicit these differences.

- *Physical equivalence*: Due to differences between human and robot embodiments, humans and robots may perform different actions to accomplish the same physical effect. For instance, even when performing the same task (soccer), humans and robots may interact with the environment in different ways (Fig. 74.3b). Humans run and kick, while robots

roll and bump. Solving this discrepancy in motor capabilities is akin to solving the *how to imitate* problem to achieve the same effect. *LfD* develops way to solve this problem. Typically, the robot may compute a path (in Cartesian space) for its end-effector that is close to the path followed by the human hand, while relying on inverse kinematics to find the appropriate joint displacements. In the football example above, this would require the robot to determine a path for its center of mass which corresponds to the path followed by the human's right foot when projected on the ground. Clearly, this equivalence is very task dependent. Recent solutions to this problem for hand motion and body motion can be found in [74.45, 46].

We can think of perceptual equivalence as dealing with the manner in which the agents perceive the world. Perceptual equivalence requires to make sure that the information necessary to perform the task is available to both humans and robots. Physical equivalence deals with the manner in which agents affect and interact with the world, so that the task is performable by both agents.

74.3 Interfaces for Demonstration

The interface used to provide demonstration plays a key role in the way the information is gathered and transmitted. We distinguish three major trends:

1. One may directly record human motions. If one is interested solely in the kinematic of the motion, one may use any of the various existing motion tracking systems, whether these are based on vision, exoskeleton, or other types of wearable motion sensors. The left-hand side of Fig. 74.4b and  VIDEO 98 show an example of full body motion tracking during walking using vision. The motion of the human body is first extracted from the background using a model of human body. This model is subsequently mapped to an avatar and then to the humanoid robot DB at ATR, Kyoto, Japan. These external means of tracking human motion return precise measurement of the angular displacement of the limbs and joints. They have been used in various works for *LfD* of full body motion [74.33, 47–49]. These methods are advantageous in that they allow the human to move freely. However, they require solutions to the correspondence problem, i.e., the problem of how to transfer motion from human to robot when both differ in the kinematic and

dynamics of their body or, in other words, if the configuration space is of different dimension and size. This is typically done when mapping the motion of the joints that are tracked visually to a model of the human body that matches closely that of the robot. Such mapping would be particularly difficult to perform when the walking machine (e.g., a hexapod) differs importantly from the human body. The problem of mapping actions across two dissimilar bodies was already evoked earlier on and refers to the correspondence problem.

2. Second, there are techniques such as kinesthetic teaching, where the robot is physically guided through the task by the human. This approach simplifies the correspondence problem by letting the user demonstrate the skill in the robot's environment with the robot's own capabilities. It also provides a natural teaching interface to correct a skill reproduced by the robot. Recent advances in skin technology offer the possibility to teach robots how to exploit tactile contact on an object (Fig. 74.4 middle and  VIDEO 104). By exploiting the compliance of the iCub robot's fingers, the teacher can teach the robot how to adapt the posture of the fingers in response to a change in tactile sensing as measured at the robot's finger tips [74.50]).

One main drawback of kinesthetic teaching is that the human must often use more degrees of freedom to move the robot than the number of degrees of freedom moved on the robot. This is visible in Fig. 74.4. To move the fingers of one hand of the robot, the teacher must use both hands. This limits the type of tasks that can be taught through kinesthetic teaching. Typically tasks that would require moving both hands simultaneously could not be taught this way. One could either proceed incrementally, teaching first the task for the right hand and then, while the robot replays the motion with its right hand, teach the motion of the left hand. However, this may prove to be cumbersome. The use of external trackers as reviewed above are more amenable to teaching coordinated motion between several limbs.

3. Third, there are immersive teleoperation scenarios, where a human operator is limited to using the robot's own sensors and effectors to perform the task. Teleoperation may be done using simple joysticks or other remote control devices, including haptic devices (Fig. 74.4 bottom and [VIDEO 101](#)). The latter have the advantage that they can allow the teacher to teach tasks that require precise control of forces, while joysticks would only provide kinematic information (position, speed).

Teleoperation is advantageous compared to external motion tracking systems, as this solves the correspondence problem entirely, since the system directly records the perception and action from the robot's configuration space. It is also advantageous compared to kinesthetic training, as it allows training the robots from a distance and is, hence, particularly suited for teaching navigation and locomotion patterns. The teacher no longer needs to share the same space with the robot. Teleoperation is, usually, used to transmit the kinematics of motion. For instance, in [74.51], the acrobatic trajectories of a helicopter are learned by recording the motion of the helicopter when teleoperated by an expert pilot. In [74.52], a robot dog is taught to play soccer by a human guiding it via a joystick. However, in recent work, teleoperation has been used successfully to teach a humanoid robot balancing techniques [74.53]. Learning to react to perturbations is done through a haptic interface attached to the torso of the demonstrator, which measures the interaction forces when the human is pushed around. The kinematics of motion of the demonstrator are directly transmitted to the robot through teleoperation and are combined with haptic information to train a model of motion conditioned on perceived forces.

The disadvantage of teleoperation techniques is that the teacher often needs training to learn to use the remote control device. Teleoperation using a simple joystick allows guiding only a subset of degrees of freedom. To control for all degrees of freedom, very complex, exoskeleton type of devices must be used, which can be cumbersome. Moreover, teleoperation prevents the teacher from observing all sensorial information required to perform the task. For instance, teleoperation, even when using haptic device, poorly renders the contacts perceived at the robot's end-effector. To palliate to this, one may provide the teacher with visualization interfaces to simulate the interaction forces.

4. Lastly, one can use explicit information, such as that conveyed by speech, to provide additional advice and comments to the demonstration [74.18, 57, 58] and [VIDEO 103](#). Speech is a very natural means of communication among humans and, hence, is viewed as an easy way to allow the end-user to communicate with robots. However, it necessitates that vocabulary that is understandable to the robot and

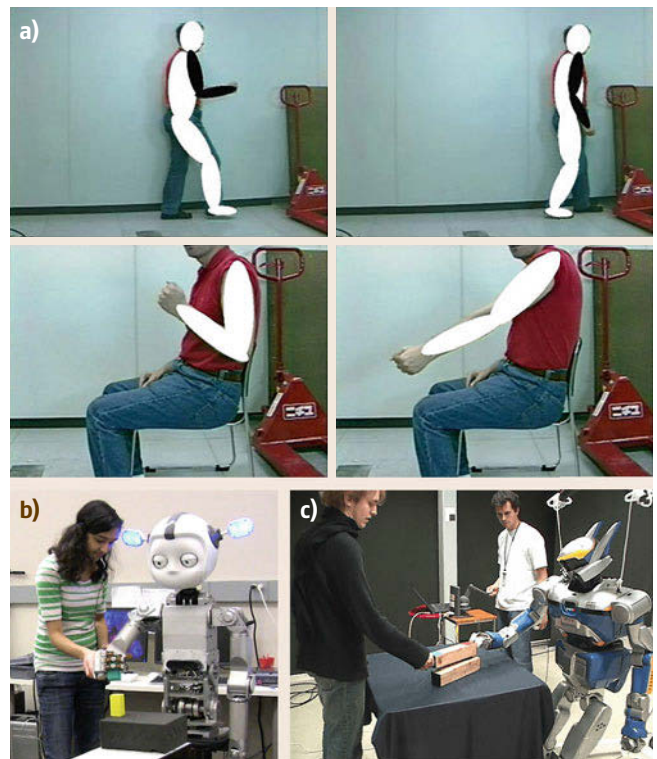


Fig. 74.4 (a) Demonstration by visual tracking of gestures (after [74.54], [VIDEO 98](#) and [VIDEO 99](#)). (b) Demonstration by kinesthetic teaching (after [74.55] and [VIDEO 104](#)). (c) Demonstration by teleoperation (after [74.56] and [VIDEO 101](#))

grounded in the actions and perceptions of the robot be defined beforehand. While this restricts teaching to discrete state–action pairs, it is particularly useful for symbolic reasoning.

Each teaching interface has its pros and cons. It is thus interesting to investigate how these interfaces could be used in conjunction to exploit complementary information provided by each modality [74.50].

74.4 Algorithms to Learn from Humans

Current approaches to encoding skills through **LfD** can be broadly divided into two trends: a low-level representation of the skill, taking the form of a non-linear mapping between sensory and motor information, and, a high-level representation of the skill that decomposes the skill into a sequence of action-perception units.

While the majority of work in **LfD** uses solely the demonstrations for learning, a growing number of works develops methods by which **LfD** can be combined with other learning techniques. One group of work investigates how to combine imitation learning with *reinforcement learning*, a method by which the robot learns through trial and error to maximize a given reward. Other works take inspiration in the way humans teach each other and introduce interactive and bidirectional teaching scenarios whereby the robot becomes an active partner during the teaching phase. We briefly review the main principles underlying each of these areas below:

74.4.1 Learning Individual Motions

Individual motions/actions (e.g., juicing an orange, trashing it, and pouring liquid into the cup in the example shown in 74.1) could be taught separately instead of simultaneously, as shown in this previous example. The human teacher would then provide one or more examples of each submotion. If learning proceeds from the

observation of a single instance of the motion/action, one calls this *one-shot* learning [74.60]. Examples of learning locomotion patterns can be found in [74.61]. To make sure that this is not akin to simple record and play, the controller is provided with prior knowledge in the form of primitive motion patterns. Learning then consists of instantiating the parameters modulating these motion patterns.

Teaching can also proceed in batch mode after recording several demonstrations, or incrementally by adding recursively more information trial by trial [74.12, 50, 62]. When learning in batch mode, learning considers all examples and draws inference by comparing the individual demonstrations. Inference is usually based on a statistical analysis, where the demonstration signals are modeled via a probability density function, exploiting various non-linear regression techniques stemming from machine learning. Popular methods these days include Gaussian processes, Gaussian mixture Models, and support vector machines.

Choosing properly the variables to encode a particular movement is crucial, as it already implies part of the solution to the problem of defining what is important to imitate. Work in **LfD** encodes human movements in either joint space, task space, or torque space [74.63–65]. The encoding may be specific to cyclic motion [74.22], discrete motion [74.21], or to a combination of both [74.61].

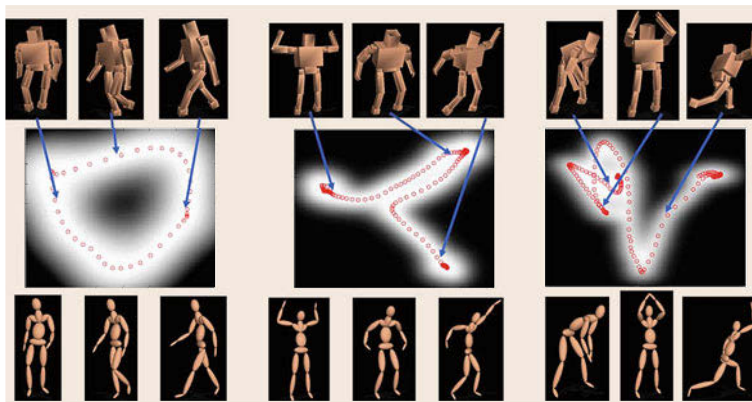


Fig. 74.5 Probabilistic encoding of motion in a subspace of reduced dimensionality (after [74.59] and VIDEO 102)

Encoding often encompasses the use of dimensionality reduction techniques that project the recorded signals into a latent space of motion of reduced dimensionality. These techniques may either perform a local linear transformations [74.66–68] or exploit global non-linear methods [74.59, 69, 70] (Fig. 74.5). Additionally, task-specific rating functions [74.71] and simulation-based optimization [74.72] are investigated to identify relevant learning features.

Teaching Force–Control Tasks

While most [LfD](#) to date work focused on learning the kinematics of motions by recording the position of the end-effector and/or the position of the robot's joints, more recently, some works have investigated transmission of force-based signals through human demonstration [74.56, 73–76]. See [VIDEO 478](#) and [VIDEO 479](#) for examples of kinesthetic teaching of compliant motion. Transmitting information about force is difficult for humans and for robots alike. Force can be sensed only when performing the task ourselves. Current efforts, hence, seek to develop methods by which one may *embody* the robot. This allows human and robot to simultaneously perceive the forces applied when performing the task. A new exciting line of research, hence, leverages on recent advances in the design of haptic devices and tactile sensing, and on the development of torque and variable impedance actuated systems to teach force-control tasks through human demonstration.

74.4.2 Learning Compound Actions

Learning complex tasks, composed of a combination and juxtaposition of individual motions, is the ultimate goal of [LfD](#). There are two major ways to proceed to learning of such complex tasks:

1. One may first learn models of all individual motions, using demonstrations of each of these actions individually. In a second stage, one may learn the right sequence and combination of these actions by observing a human performing the whole task. This approach, however, assumes that one can list all necessary individual actions, so-called *primitive* actions. To date, there does not exist a database of such primitive actions and one may wonder whether the variability of human motion may really be reduced to a finite list of possible motions. A common approach is to first learn models of all of the individual motions, using demonstrations of each of these actions individually [74.77, 78], and then learn the right sequencing/combination in a second stage either by observing a human performing the whole task [74.79, 80] or through reinforcement learning [74.81]. However, this approach assumes that there is a known set of all necessary primitive actions. For specific tasks this may be true, but to date there does not exist a database of general purpose primitive actions, and it is unclear whether the variability of human motion may really be reduced to a finite list.
2. The alternative is to observe the human performing the complete task and to automatically segment the task to extract the primitive actions, which may then become task-dependent, see e.g., [74.82, 83]. This has the advantage of learning, in one swipe, both the primitive actions and the way they should be combined. One issue that arises is that the number of primitive tasks is often unknown, and there could be multiple possible segmentations that must be considered [74.52].

Other examples include learning how to sequence known behaviors to enable complex navigation tasks through the imitation of a more knowledgeable robots or humans [74.9, 84, 85] and learning how to sequence primitive motions for full body motion in humanoid robots [74.25, 33, 86].

A large body of these works uses a symbolic representation of both the learning and the encoding of the task [74.6, 30, 85, 87–91]. This symbolic way of encoding skills may take several forms. One common way is to segment and encode the task according to sequences of *predefined* actions, described symbolically. Encoding and regenerating the sequences of these actions can, however, be done using classical machine learning techniques, such as [HMM](#), [74.30].

Often, these actions are encoded in a hierarchical manner. In [74.85], a graph-based approach is used to generalize an object moving skill, using a wheeled mobile robot. In this model, each node in the graph represents a complete behavior and generalization takes place at the level of the topological representation of the graph. The latter is updated incrementally.

References [74.88, 89] follow a similar hierarchical and incremental approach to encode various household tasks (such as setting the table and putting dishes in a dishwasher) (Fig. 74.6 and [VIDEO 103](#)). There, learning consists in identifying a sequence of predefined, elementary actions, which is further combined into a hierarchical task network. By analyzing multiple demonstrations, the ordering of elementary actions is learned, resulting in a precedence graph. The precedence graph defines a partial ordering on the set of learned elementary actions, which can be exploited to execute elementary actions in parallel, extracting symbolic rules that manage the way each object must be

handled. In [74.92], the approach was extended to learning subsymbolic goal and constraint descriptions for each elementary action. In the execution phase, the robot applies motion planning to generate a motion to reach the goals while obeying the constraints. The resulting task description mimics the strategy that humans follow when performing the task. Based on the subsymbolic goal and constraint descriptions, the robot can reason to adapt the strategy to changes in object location, obstacle occurrence, and varying start configurations.

The approaches reviewed above assume a deterministic world, where actions unfold uniquely from perception of the current state of the world. However, robots operating in real environments will observe the world using imperfect sensors and the effects of their actions may be stochastic. To account for the stochasticity of the robot's perceptions and actions, *Schmidt-Rohr et al.* [74.93] use a model of the task with partially observable Markov decision processes (POMDP). At run time, an optimal (in a maximum likelihood sense) decision is then taken.

Reference [74.90] exploits also a hierarchical approach to encoding a skill in terms of pre-defined behaviors. The skill consists in moving through a maze where a wheeled robot must avoid several kinds of obstacles and reach a set of specific subgoals. The particularity of this approach lies in the use of symbolic representations of the skill, which are applied to explore the role of the teacher in guiding incremental learning of the robot.

Finally, [74.91] took a symbolic approach to encoding human motions as sets of pre-defined postures, positions, or configurations, considering different levels of granularity for the symbolic representation of the motion. This a priori knowledge is then used to explore the correspondence problem through several simulated setups, including motion in joint space of arm links and displacements of objects on a two-dimensional (2-D) plane.

The main advantage of these symbolic approaches is that high-level skills (consisting of sequences of symbolic cues) can be learned efficiently through an interactive process. However, because of the symbolic nature of their encoding, the methods rely on a large amount of prior knowledge to predefine the important cues and to segment those efficiently.

74.4.3 Incremental Teaching Methods

The statistical approach described previously is an interesting way to extract autonomously the important features of the task, and, thus to avoid putting too much prior knowledge in the system. However, it requires a large number of demonstrations to draw statistically valid inference. It is not reasonable to assume that a layuser will perform many demonstrations of the same task. Hence, for LfD to be amenable to lay users, learning should require as few demonstrations as possible. Ideally, one would like the robot to be bootstrapped with some initial knowledge, so that the robot can start

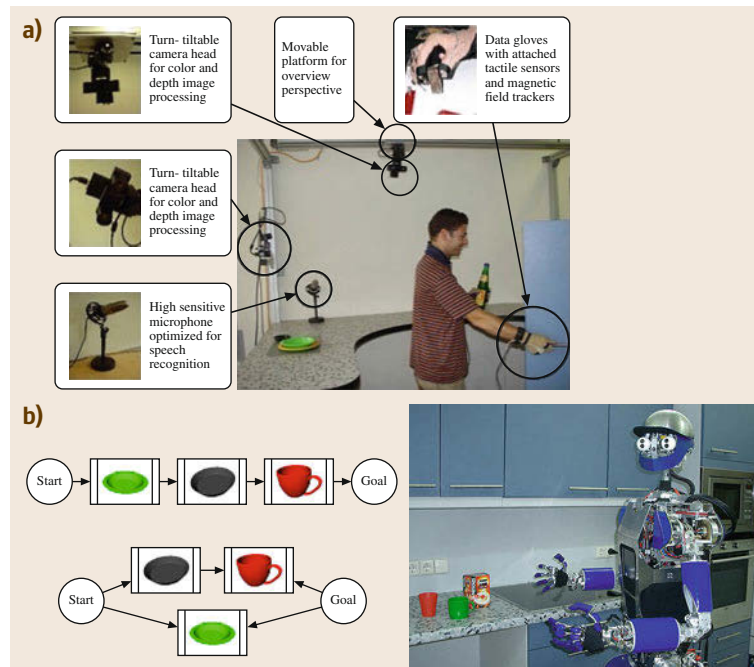


Fig. 74.6 (a) Training center with dedicated sensors. (b) Precedence graphs learned by the system for the *setting the table* task. (c) Initial task precedence graph for the first three demonstrations. (d) Final task precedence graph after observing additional examples (after [74.88]) (VIDEO 103)

right away to perform the task, and human training would be used solely to help the robot gradually improve its performance.

Incremental learning approaches that gradually refine task knowledge as more examples become available pave the way towards **LfD** systems suitable for such continuous and long-life robot learning. Figure 74.7 and [VIDEO 104](#) shows an example of such incremental teaching of a simple skill.

These incremental learning methods use various forms of deixis, as well as verbal and non-verbal interactions, to guide the robot's attention to the important parts of the demonstration or to particular mistakes produced by the robot during the reproduction of the task. Such incremental and guided learning is often referred to as *scaffolding* or *molding* of the robot's knowledge, and is key to teaching robots tasks of increasing complexity [74.90, 94].

Research on the use of incremental learning techniques for robot **LfD** has contributed to the development of methods for learning complex tasks within the household domain from as few demonstrations as possible. Moreover, it has contributed to the development and application of machine learning that allow a continuous and incremental refinement of the task model. Such systems have sometimes been referred to as *background knowledge-based* or *EM deductive LfD-systems*, as presented in [74.95, 96]. They usually require very few or even only a single user demonstration to generate executable task descriptions. The main objective of this line of research is to build a meta-representation of the knowledge that the robot has acquired on the task and to apply reasoning methods on this knowledge database (Fig. 74.6). In this scenario, reasoning involves recognizing, learning, and representing repetitive tasks.

Pardowitz et al. [74.97] discuss how different forms of knowledge can be balanced in an incremental learning system. The system relies on building *task precedence graphs*. Task precedence graphs encode hypotheses that the system makes on the sequential structure of a task. Learning of the task precedence graphs allows the system to schedule its operations most flexibly,

while still meeting the goals of the task ([74.98] for details). Task precedence graphs are directed, acyclic graphs that contain a temporal precedence relation that can be learned incrementally. Incremental learning of task precedence graphs leads to a more general and flexible representation of the task knowledge (Fig. 74.6 and [VIDEO 105](#)).

74.4.4 Combining Learning from Humans with Other Learning Techniques

To recall, a main argument for the development of **LfD** methods was that they would speed up learning by providing examples of *good solutions*. This assumption, however, is realistic only if the context for the reproduction is sufficiently similar to that of the demonstration. We saw previously that the use of dynamical systems-based representation at the trajectory level allows the robot to depart to some extent from a learned trajectory to reach the target, even when both the object and the hand of the robot have moved from the location shown during the demonstration. There are, however, situations in which such an approach would fail, such as, for instance, when placing a large obstacle in the robot's pathway (Fig. 74.8). Besides, robots and humans may differ significantly in their kinematics and dynamics of motion and, although there are varieties of ways to bypass the so-called correspondence problem, relearning a new model may still be required in special cases.

To allow the robot to relearn to perform a task in any new situation, it appeared important to combine **LfD** methods with other motor learning techniques. Reinforcement learning (**RL**) appeared particularly suitable for type of problem. Indeed, imitation learning is limiting in that it requires the robot to learn only from what has been demonstrated. Reinforcement learning, in contrast, allows the robot to discover new control policies through free exploration of the state-action space. Approaches that combine imitation learning and reinforcement learning aim at exploiting the strength of both algorithms to overcome their respective drawbacks. Demonstrations are used to guide the exploration

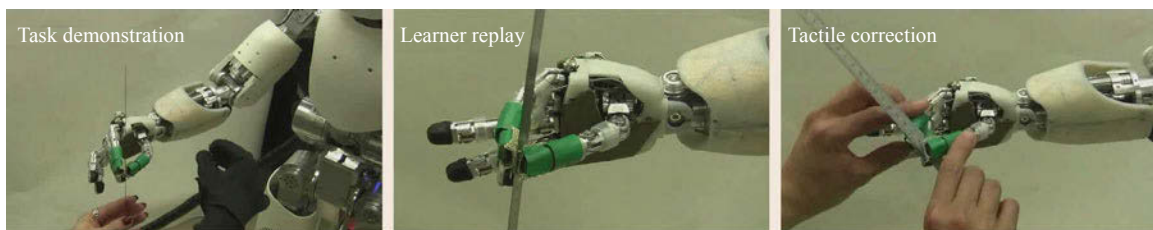


Fig. 74.7 An incremental learning strategy where a manipulation skill is first demonstrated through the use of a data glove. After a first reproduction trial, the skill is refined through kinesthetic teaching, by exploiting the tactile capabilities of the iCub humanoid robot (after [74.50]) ([VIDEO 104](#))

in reinforcement learning (RL). This, hence, reduces the time it takes for RL algorithms to find an adequate control policy, while allowing the robot to depart from the demonstrated behavior. Figures 74.8 show two examples of techniques that use reinforcement learning in conjunction with LfD to improve the robot's performance beyond that of a demonstrator.

Early work on LfD using RL started in the 1990s with learning to swing up and control an inverse pendulum [74.100] and learning industrial tasks like peg-in-hole with a robot arm [74.26]. More recent efforts include [74.101–103], who tackled robust control of the upper body of humanoid robots in various manipulation tasks, learning an archery skill [74.104], and learning how to hit a snooker ball [74.105].

Demonstrations can be used in different ways to bootstrap RL. They may be used as initial roll-outs from which an initial estimate of the policy is computed [74.106–108], or to generate an initial set of primitives [74.81, 103, 107]. In the latter case, RL is then used to learn how to select across these primitives. Demonstrations can also be used to limit the search space covered by RL [74.101, 109], or to estimate the reward function [74.110, 111]. Finally, RL and imitation learning can be used in conjunction at run time, by letting the demonstrator take over part of the control during one trial [74.112].

Another way to enable the robot to learn a control strategy through a combination of self-experimentation and learning from watching others is to evolve population of agents that mimic each other. Such an evolutionary approach using genetic algorithms has been investigated by a number of authors, e.g., for learning of manipulation skills [74.113], navigation strategies [74.114], or sharing a common vocabulary to name sensoriperception and actions [74.115].

Variants on Reinforcement Learning

While most of the works that combine imitation learning with reinforcement learning assume the reward to be known, inverse reinforcement learning (IRL) offers a framework to determine automatically the reward and the optimal control policy [74.116]. When using human demonstrations to guide learning, IRL solves jointly

the *what to imitate* and *how to imitate* problems. Other approaches to estimating the reward or cost function automatically have been proposed, see, for instance, the maximum margin planning technique [74.117] and the automatic extraction of constraints [74.118].

Underlying all IRL works is the assumption of a consistent reward function. When demonstrations are provided by multiple experts, this assumes that all experts optimize the same objectives. This is constraining and does not exploit the variability of ways in which humans may solve the same task. Recent IRL works consider multiple experts and identify multiple different reward functions [74.119, 120]. This allows the robots to learn multiple (albeit suboptimal) ways to perform the same task. The hope is that this multiplicity of policies will make the controller more robust, offering alternative ways to complete the task, when the context no longer allows the robot to perform the task in the optimal way.

The vast majority of work on LfD relies on successful demonstrations of the desired task by the human. It hence assumes that all the demonstrations are good demonstrations and discards those that are poor proxy of what would be deemed as a good demonstration. Recent work has also investigated the possibility that demonstrations may instead be failed attempts at performing the task [74.121, 122]. Learning then proceeds from observing solely incorrect demonstrations (VIDEO 476 and VIDEO 477). Note that demonstrations are never completely incorrect. Learning from failed demonstration then attempts to discover which parts of the demonstrations were correct and which were incorrect, so as to improve solely the incorrect parts. In this context, LfD addresses the questions of *what to* and *what not to* imitate. It offers an interesting alternative to approaches that combine imitation learning and reinforcement learning, in that no reward needs to be explicitly determined.

74.4.5 Learning from Humans, a Form of Human–Robot Interaction

Another perspective adopted by LfD to make the transfer of skill more efficient is to focus on the interaction

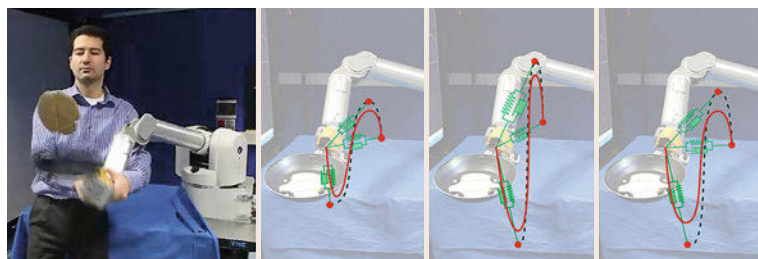


Fig. 74.8 Illustration of the use of reinforcement learning in policy parameter space to refine a skill initially learned from demonstration (after [74.99] and VIDEO 105)

aspect of the transfer process. As this transfer problem is complex and involves a combination of social mechanisms, several insights from human–robot interaction (HRI) were explored to make efficient use of the teaching capabilities of the human user, [74.123–125] for surveys. Next, we briefly survey some of these works.

The development of algorithms for detecting *social cues* given implicitly or explicitly by the teacher during training and the integration of those as part of other generic mechanisms for LfD has become the focus of a large body of work in LfD. Such social cues can be viewed as a way to introduce priors in a statistical learning system, and, by so doing, to speed up learning. Indeed, several hints can be used to transfer a skill not only by demonstrating the task multiple times but also by highlighting the important components of the skill. This can be achieved by various means, using different modalities.

A large body of work explored the use of pointing and gazing (Fig. 74.9 left and VIDEO 106) as a way of conveying the intention of the user [74.79, 126–132]. Vocal deixis, using a standard speech recognition engine, has also been explored widely [74.79, 133]. In [74.88], the user makes vocal comments to highlight the steps of the teaching that are deemed as being the most important. In [74.134, 135], only the prosody of the speech pattern is looked at, rather than the exact content of the speech, as a way to infer some information on the user’s communicative intent.

In [74.136], these social cues are learned through an imitative game, whereby the user imitates the robot. This allows the robot to build a user-specific model of these social pointers, and, hence be more robust to detecting those.

Recent lines of research in interactive LfD seeks to give a more active role to the teacher in a bidirectional teaching process [74.15, 137, 138]. Robots become more active partners and can indicate which portion of the demonstration was unclear. Teachers may in turn refine the robot’s knowledge by providing complementary information where the robot is performing poorly. This supplementary information may consist of additional rounds of demonstrations of the complete task [74.139], or may be limited to subparts of the task [74.140, 141]. The information can be conveyed through specific task’s features, such as a list of waypoints [74.142]. The robot is then left free to interpolate a trajectory using these key points.

The design of such incremental teaching methods calls for machine learning techniques that enable the incorporation of new data in a robust manner. It also opens the door to the design of other human–robot interfacing systems, including the use of speech, which leads to meaningful dialogs between humans and robots. An example of such bidirectional teaching is given on the right-hand side of Fig. 74.10. The robot asks for help during or after teaching, verifying that its understanding of the task is correct [74.14]. This teaching interaction is tailored to let the user become an active participant in the learning process (and not only a model of expert behavior).

By taking inspiration from the human tutelage paradigm, [74.15] shows that a socially guided approach can improve both the human–robot interaction and the machine learning process by taking into account *human benevolence*. That work highlights the role of the teacher in organizing the skill into manageable steps and maintaining an accurate mental model

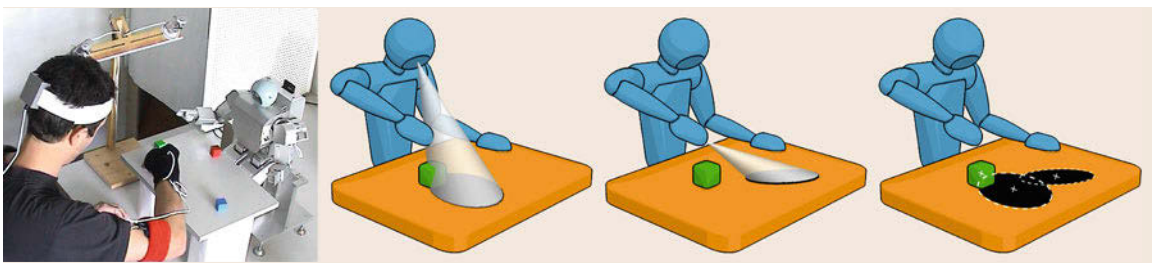


Fig. 74.9 Illustration of the use of social cues to speed up the imitation learning process. Here, gazing and pointing information are used to select probabilistically the objects relevant for the manipulation skill (VIDEO 106)

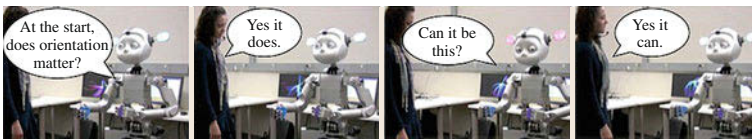


Fig. 74.10 Example of an active teaching scenario. The robot asks for help during or after teaching, verifying that its understanding of the task is correct (after [74.14]) (VIDEO 107)

of the learner's understanding. Reference [74.138] use a similar teaching paradigm and extend the concept to the learning of continuous motion trajectories and of actions on objects, and propose experiments where a humanoid robot learns new manipulation skills by first observing a human demonstrator (through motion sensors) and then gradually refining its skill through teacher support. In this application, the user provides scaffolds to the robot for the reproduction of the skill by moving kinesthetically a subset of the motors. Through the supervision of the user who progressively dismantles the scaffolds after each reproduction attempt, the robot can finally reproduce the skill on its own. Reference [74.143] highlights the importance of an active participation of the teacher not only to demonstrate a model of expert behavior but also to refine the acquired motion through spoken feedback.

Reference [74.90] provides experiments where a wheeled robot is teleoperated through a screen interface to simulate a *molding* process, that is, by letting the robot experience sensory information when exploring its environment through the teacher's support. Their model uses a memory-based approach in which the user provides labels for the different components of the task to teach hierarchically high-level behaviors.

Finally, a core idea of the HRI approach to LfD is that imitation is goal directed, that is, actions are meant to fulfill a specific purpose and to convey the intention of the actor [74.144]. While a longstanding trend in LfD approached the problem from the standpoint of

trajectory following [74.84, 145, 146] and joint motion replication, [74.147–150], recent works, inspired by the above rationale, start from the assumption that imitation is not just about observing and replicating the motion, but rather about *understanding* the goals of a given action (see the above survey of approaches to determining automatically the reward or what to imitate).

Determining the way humans learn to both extract the goals of a set of observed actions and give these goals a hierarchy of preference is fundamental to our understanding of the underlying decisional process to imitation. While we have surveyed recent work in that area, it is important to recall other approaches to tackling these issues that have previously followed a probabilistic approach to explain the derivation and sequential application of goals and apply this to enable learning of manipulatory tasks requiring sequencing of subsets of goals [74.97, 145, 151, 152].

Understanding the goal of the task is still only half of the picture, as there may be several ways of achieving the goal of the task. Moreover, what is feasible (or optimal) for the demonstrator may not necessarily be appropriate for the imitator [74.36]. Thus, different models, modes and communication channels, should be used in conjunction to find a solution that is optimal both from the point of view of the imitator and that achieves what the demonstrator seeks to teach the robot.

This concludes our survey. As the reader can see, the issues of what and how to imitate are tightly connected and to a large extent remain only partly solved.

74.5 Conclusions and Open Issues in Robot LfD

Research in LfD or programming by demonstration (PbD) is progressing rapidly, pushing back limits and posing new questions all the time. As such, any list of limitations and open questions is bound to be incomplete and out of date. However, there are a few long-standing limitations and open questions that bear further attention.

Generally, work in LfD assumes a fixed, given form for the robot's control policy, and learns appropriate parameters. To date, there are several different forms of policies in common usage, and there is no clear correct (or dominant) technique. Furthermore, it is possible that a system could be provided with multiple possible representations of controllers and select which is most appropriate.

The combination of reinforcement learning and imitation learning has been shown to be effective in addressing the acquisition of skills that require fine tuning of the robot's dynamics. Likewise, more interactive

learning techniques have proven successful in allowing for collaborative improvement of the learnt policy by switching between human-guided and robot-initiated learning. However, there do not yet exist protocols to determine when it is best to switch between the various learning modes available. The answer may, in fact, be task dependent.

In work to date, teaching is usually done by a single teacher, or teachers with an explicit concept of the task to teach. More work needs to be done to address issues related to conflicting demonstrations across teachers with different styles. Similarly, teachers are usually human beings, but could instead be an arbitrary expert agent. This agent could be a more knowledgeable robot or a computer simulation. Finally, another relatively little explored question relates to the problem of how to transfer skills across multiple agents, including multiple robots (i. e., teaching is done from a teacher robot to various learner robots). Early work in this direction was

done in the 1990s [74.115, 153, 154]. This work, however, has so far been reduced to transfer of navigation or communication skills across swarms of simple mobile robots.

Experiments in LfD have mostly focused on a single task (or set of closely related tasks), and each experiment starts with a tabula rasa. As learning of

complex tasks progresses, means to store and reuse prior knowledge at a large scale will have to be devised. Learning stages, akin perhaps to those found in child development, may be required. There will need to be a formalism to allow the robot to select information, to reduce redundant information, select features, and store new data efficiently.

Video-References

-  VIDEO 29 Demonstrations and reproduction of the task of juicing an orange available from <http://handbookofrobotics.org/view-chapter/74/videodetails/29>
-  VIDEO 97 Demonstrations and reproduction of moving a chessman available from <http://handbookofrobotics.org/view-chapter/74/videodetails/97>
-  VIDEO 98 Full-body motion transfer under kinematic/dynamic disparity available from <http://handbookofrobotics.org/view-chapter/74/videodetails/98>
-  VIDEO 99 Demonstration by visual tracking of gestures available from <http://handbookofrobotics.org/view-chapter/74/videodetails/99>
-  VIDEO 100 Demonstration by kinesthetic teaching available from <http://handbookofrobotics.org/view-chapter/74/videodetails/100>
-  VIDEO 101 Demonstration by teleoperation of humanoid HRP-2 available from <http://handbookofrobotics.org/view-chapter/74/videodetails/101>
-  VIDEO 102 Probabilistic encoding of motion in a subspace of reduced dimensionality available from <http://handbookofrobotics.org/view-chapter/74/videodetails/102>
-  VIDEO 103 Reproduction of dishwasher unloading task based on task precedence graph available from <http://handbookofrobotics.org/view-chapter/74/videodetails/103>
-  VIDEO 104 Incremental learning of finger manipulation with tactile capability available from <http://handbookofrobotics.org/view-chapter/74/videodetails/104>
-  VIDEO 105 Policy refinement after demonstration available from <http://handbookofrobotics.org/view-chapter/74/videodetails/105>
-  VIDEO 106 Exploitation of social cues to speed up learning available from <http://handbookofrobotics.org/view-chapter/74/videodetails/106>
-  VIDEO 107 Active teaching available from <http://handbookofrobotics.org/view-chapter/74/videodetails/107>
-  VIDEO 476 Learning from failure I available from <http://handbookofrobotics.org/view-chapter/74/videodetails/476>
-  VIDEO 477 Learning from failure II available from <http://handbookofrobotics.org/view-chapter/74/videodetails/477>
-  VIDEO 478 Learning compliant motion from human demonstration available from <http://handbookofrobotics.org/view-chapter/74/videodetails/478>
-  VIDEO 479 Learning compliant motion from human demonstration II available from <http://handbookofrobotics.org/view-chapter/74/videodetails/479>

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75. Biologically Inspired Robotics

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Throughout the history of robotics research, nature has been providing numerous ideas and inspirations to robotics engineers. Small insect-like robots, for example, usually make use of reflexive behaviors to avoid obstacles during locomotion, whereas large bipedal robots are designed to control complex human-like leg for climbing up and down stairs. While providing an overview of bio-inspired robotics, this chapter particularly focus on research which aims to employ robotics systems and technologies for our deeper understanding of biological systems. Unlike most of the other robotics research where researchers attempt to develop robotic applications, these types of bio-inspired robots are generally developed to test unsolved hypotheses in biological sciences. Through close collaborations between biologists and roboticists, bio-inspired robotics research contributes not only to elucidating challenging questions in nature but also to developing novel technologies for robotics applications. In this chapter, we first provide a brief historical background of this research area and then an overview of ongoing research methodologies. A few representative case studies will detail the successful instances in which robotics technologies help identifying biological hypotheses. And finally we discuss challenges and perspectives in the field.

Biologically inspired robotics (or bio-inspired robotics in short) is a very broad research area because almost all robotic systems are, in one way or the other, inspired from biological systems. Therefore, there is no clear distinction between bio-inspired robots and the others, and there is no commonly agreed definition [75.1]. For example, legged robots that walk, hop, and run are usually regarded as bio-inspired robots because many

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biological systems rely on legged locomotion for their survival. On the other hand, many robotics researchers implement biological models of motion control and navigation onto wheeled platforms, which could also be regarded as bio-inspired robots [75.2].

75.1 General Background

The broad spectrum of bio-inspired robotics research is reflected to a variety of synonyms used in different scientific communities. For example, biomimetics and bionics are usually used to represent the types of research in which researchers observe biological systems and extract design principles for robotic applications. The terms bio-robotics and bio-engineering are also used interchangeably to biomimetics and bionics, but they often refer to engineered solutions specifically for biomedical applications. Another approach, usually classified as artificial life, biological cybernetics, or biophysics, investigates biological systems by using synthetic approaches. Here biological systems are typically viewed as mechanical and chemical entities and characterized by mechanistic models that are often very similar to the bio-inspired robots. The definitions and types of research studies conducted in these research areas are often overlapping, and many research projects provide results across the different areas.

While some of these research areas are also covered in the other chapters of this handbook, one of the most prominent, and more importantly useful, aspects of bio-inspired robotics lies in the contributions of robotics research for biological sciences. In contrast to the other robotics research, a significant number of bio-inspired robots were developed for the purpose of testing hypotheses concerning biological systems and for identifying the underlying mechanisms of biological systems that are very difficult to be clarified otherwise. In this chapter, we specifically focus on this aspect of bio-inspired robotics.

75.1.1 Brief History and Conceptual Background

There is a long history of the engineers' desire to replicating biological systems into artificial ones, including the famous examples of Japanese Karakuri dolls and Swiss automata several centuries ago (Fig. 75.1). Similarly, scientific efforts to use robotic systems to understand biological systems have also a relatively long history, which goes back even before the modern robotics started. One of the most influential examples in the earlier ages can be represented by the works in the field of cybernetics in which a number of system theories such as the concepts of feedback and feedforward were applied to understand phenomena in biological systems [75.3, 4].

The rise of neuroscience in the mid-twentieth century influenced bio-inspired robotics research significantly. In the 1950s, one of the first bio-inspired robots, Tortoises, was built by Grey Walter, a neurophysi-

ologist. The work was mainly driven by biological questions, such as how a simple neuron connectivity can result in richness of sensory-motor behaviors, and a turtle-like robot consisting of analog electronics, sensors, and electric motors demonstrated reflexive behaviors as well as basic motor learning in autonomous robots [75.5]. Another physiologist, *Valentino Braitenberg*, also explored the power of *understanding by building* approach, which led to the famous thought experiments of Braitenberg Vehicles, i.e., a series of imaginary mobile robots that are still often used to teach the relationship between neural connectivity and sensory-motor behaviors [75.6].

The invention of digital computers was also another historical milestone in bio-inspired robotics. The pioneers of digital computers such as *John von Neumann* and *Alan Turing* provided significant influences in the biological studies through their seminal works on self-replication and self-organization [75.7, 8], and the subsequent foundation of the field of Artificial Intelligence in the 1950s was driven based on the understanding of human intelligence especially from the computational standpoint [75.9].

While the power of digital computers dominated bio-inspired robotics for a while, the study of insect-like reflexive behaviors became popular again in the 1980s with the emergence of behavior-based robotics. The intensive studies of this approach shed light on the massively parallel nature of motion control processes, and demonstrated behaviors that cannot be fully explained by the conventional *sense-think-act* style control approach [75.10, 11]. One of the main contributions of this line of studies lies in the fact that the diversity and flexibility of control architecture is essential in adaptive behaviors in real-world systems, and the complexity of behaviors is not necessarily originated in the complexity of controller but in physical system–environment interactions [75.12].

Since then the research on physical system–environment interactions has been very popular in the interdisciplinary community of embodied cognitive science and artificial intelligence in which roboticists, biologists, computer scientists, and physicists work together to look into further details of underlying mechanisms of adaptivity in biological systems. Here the body as a physical entity is not only considered as a necessary *container* of intelligent adaptive behaviors but it also plays a central role that induces self-organization of patterns and structures in adaptive intelligent behaviors [75.13–15]. In this context, robotics methodologies and technologies are used to investigate hypotheses about the roles of embodiment that cannot be easily tested in animals.

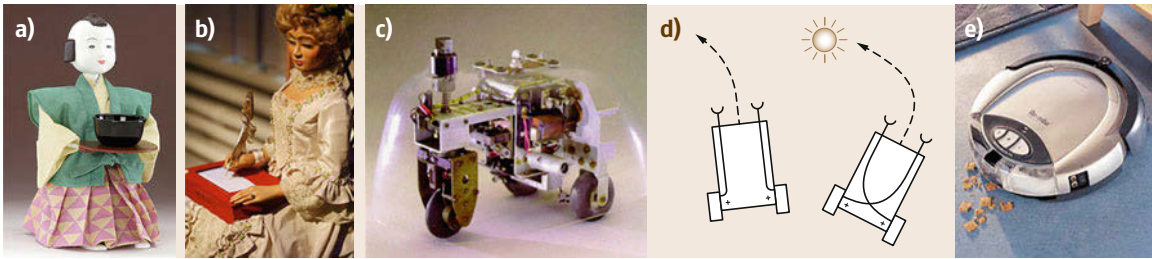


Fig.75.1a–e Examples of bio-inspired robots in the history. (a) Japanese Karakuri doll, (b) Swiss Automaton, (c) Grey Walter's Tortoises Robot (after [75.5]), (d) Braitenberg Vehicle (after [75.6]), and (e) a cleaning robot Roomba as an example of behavior-based robotics application

75.2 Methodology

In order to provide contributions to both robotics and biological sciences, bio-inspired robotics research usually follows a series of unique research processes which are not necessarily common to the other areas of robotics. This section first explains similarities and differences in robotics and biology research, and then introduces a set of important concepts, methodology, and research tools often used in the bio-inspired robotics.

75.2.1 Similarities and Differences in Robotics and Biology

Both robotics and biological research aim to obtain the basic understanding about autonomous and adaptive behaviors of complex systems, thus the scientific methodologies of these fields are usually very similar. For example, biologists usually start with finding an interesting problem in animals, that can be comparable to roboticists building robot prototypes of their interests as the first step of research. Second, the animals are carefully observed such that the underlying mechanisms can be efficiently and effectively analyzed, a step which roboticists also follow in the case of their robots. And finally, both biologists and roboticists develop hypothetical models to explain the mechanisms of their interests and test them through additional experiments and analyses. Here the modeling processes are also similar in both robotics and biology in a sense that they typically employ similar scientific methods, such as dynamics modeling tools, computational optimization techniques, and the other analysis methods of system engineering, for example.

There are, however, a number of fundamental differences in biological and robotics research, which are mostly originated in the fact that biological systems are *constructed* by considerably different design principles in nature. Although it is very difficult to cover all differences, the following aspects of biological systems

characterize some of the major discrepancies from today's robotic systems.

Multipurpose Systems in Unstructured and Uncertain Environment

In contrast to most of the robotic systems that are designed to perform one type of task in a well-defined environment, all biological systems are intrinsically multipurpose systems that are designed for many tasks in undefined and uncertain environments. For example, animals need to process tasks such as regulating metabolism for self-sufficiency, protecting themselves from predators, mating, and reproducing. It is important for roboticists to know that (i) animals are not optimized for one of these tasks, but they are designed to conduct all of them, and (ii) they do so in a way that is not optimal in any sense, but just *good enough* to survive and reproduce. Therefore, it is often not a good idea to blindly copy a part of animals' designs and mechanisms into robotic systems because there could be an alternative optimal solution if the system has to do a single task in a well-defined environment. Robotics researchers are, however, able to learn many principles and mechanisms from biological systems, if they are interested in the systems that need to deal with many tasks in unstructured and uncertain environments.

Massively Parallel, Modular, and Redundant Structures

Biological systems are composed of highly redundant structures in their bodies [75.13]. For example, most of multicellular organisms have massively parallel muscle fibers constituting a muscle group, a skeletal joint controlled through multiple muscle groups, millions of nerve cells conducting parallel signal processing, and countless receptors sensing changes in the environment. If compared to our robotic systems today, biological systems have orders of magnitude larger numbers of

such sensory, actuation, and computational units that have to be carefully considered in bio-inspired robotics research. In addition, the processes necessary for autonomy and adaptivity are generally highly decentralized in biological systems. The control of animals' arms and legs, for example, involves mechanical interactions of musculoskeletal structures, reflexive sensory-motor pathways in spinal cord, and more complex motion control and planning in the higher centers of nervous systems, which are running in parallel. The redundant structures of biological systems also provide an important discrepancy between animals and today's robots: most of the subsystems in a living organisms have great autonomy and adaptivity by themselves, as exemplified by the fact that individual cells in skins and bones as well as receptors and muscles have their own regulation mechanisms as metabolism and growth.

Self-Organization and Dynamic Changes of Entire Organisms

Another important discrepancy between animals and today's robots lies in the fact that there is no *human designers* behind animals, and all components in an organism have to be designed, assembled and repaired by itself. Consequently, every individual animal has to start its life smaller and gradually grow larger over time; every part of their bodies is continuously changing; sensory-motor control has to be continuously updated to reflect the changes in the bodies. It is particularly important for robotics researchers to consider that there are different timescales in these dynamic processes in biological systems (Fig. 75.2 [75.16]). Some of the different timescales can be represented by the continuous changes of body plans at the evolutionary processes, the changes of body sizes and muscle strength through ontogenetic timescale, and update of sensory-motor loops in here and now timescale.

75.2.2 Modeling Biological Systems

Modeling plays an essential role in biological sciences. Biological models are the representation of knowledge which is not only used to communicate scientific discoveries among researchers but also structuring research areas by labeling knowns and unknowns. To make research activities efficient and effective, there are many different ways to model biological systems such as descriptive/illustrative explanations, mathematical, physical, or chemical representations. From this perspective, the researchers in bio-inspired robotics have been exploring whether robotic platforms can be used as a scientific tool to develop models of biological systems, which leads to an alternative approach to elucidating biological hypotheses (Fig. 75.3). Robots are

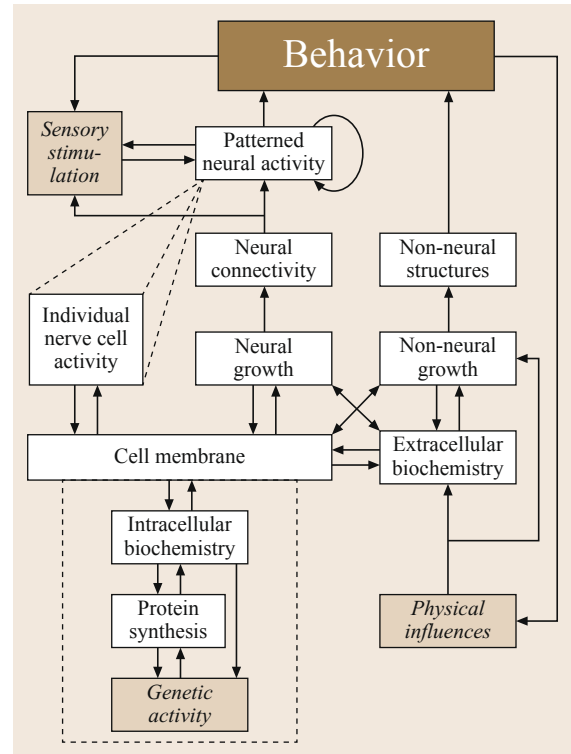


Fig. 75.2 Elements and their interactions that influence behaviors in biological systems. The model includes both neural and non-neural elements such as hormones (which constitute part of the extracellular biochemistry), bones, muscles, sensors, and their ontogenetic processes (after [75.16])

useful because they are physical entities as compared to simulated ones. First of all, by building models that can be implemented in a physical system, the process ensures whether the model in question is physically meaningful or not. In contrast, computationally simulated models always involve many approximations and simplifications which might affect the realism and therefore usefulness of the model (e.g., correctly modeling the hydrodynamics of a swimming fish is very hard in a simulation while it *comes for free* in a fish robot). Second, building robots directly contributes to the development of unconventional technological components.

Having said that, the use of robots as a scientific tool for biology is challenging because of the considerable discrepancies between animals and robots as explained in the previous subsection. A superficial copy of biological systems into a robotic counterpart is not a good idea because robots usually functions based on a completely different set of mechanisms, and the developed robot would most likely not explain much about the underlying mechanisms of biological

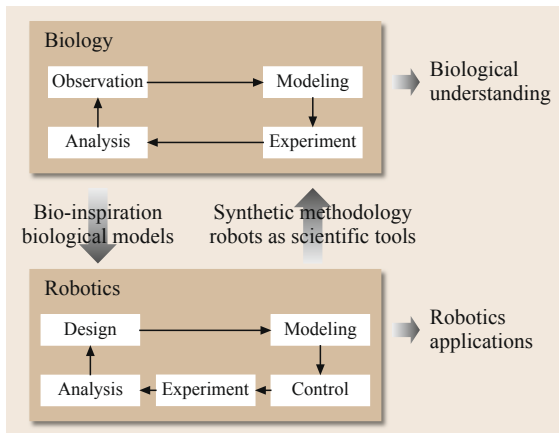


Fig. 75.3 Overview of bio-inspired robotics. Both biology and robotics follow similar research methods and interact to each other through models and tools, while they contribute to different objectives, i. e., understanding of biological systems or development of robotic applications

systems. Instead, it is particularly important to carefully examine what biological hypothesis we are interested in and we are testing by building robotic platforms. As an extreme example, if one is interested in understanding navigation mechanisms of animals, it is usually better to start with wheeled robot platforms than legged or flying ones, because the latter platforms would introduce unnecessary complexity in the research to examine a given hypothesis.

It is, however, not a trivial problem to find good biological hypotheses that can be applied in the bio-inspired robotics research. Biological systems are generally very complex, and hypotheses are not clearly separable from one question to another. Behaviors of animals are, for example, a result from neuronal activi-

ties of short and long terms, musculoskeletal dynamics, genetic and social interactions, and the mechanisms could also significantly vary in different individuals or species.

In order to deal with such a complexity in nature, *Full* and *Koditschek* have proposed an insightful methodology [75.17]. As shown in Fig. 75.4, they proposed a two-level modeling process which could benefit bio-inspired robotics research greatly: in the first level, a model should be simplified as much as possible such that it can be generalized over many species or in a large scale without being bothered too much by the details of complex animal structures. These models are called *templates*. A good example of this kind is the so-called spring-mass model that characterizes running behaviors of many different types of legged animals, even though it is an extremely simple model consisting of a point mass and a linear spring only. This approach enables researchers to examine the basic principles in nature, and despite its simplicity, the model can explain behavioral characteristics in a wide variety of animals even without considering detailed anatomical discrepancies between species. In the second level of modeling processes, templates should be enhanced by more details, which are called *anchors*. The investigations of the anchors are generally intended for more specific questions by adding redundancies of muscles or limbs or implementing more complex neuromuscular circuitry, for example. Through the template–anchor research approach, a research area can be effectively structured, and, for bio-inspired robotics research in particular, the simplified models can benefit robotics engineers to replicate behaviors of biological systems in a conceptual level.

Independently from the simplicity, it is also important to consider the purposes of models which

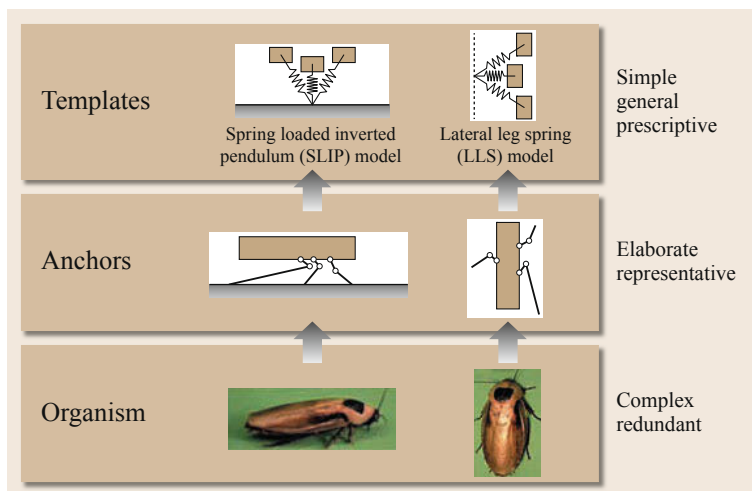


Fig. 75.4 Modeling hierarchy exemplified by the legged locomotion models. Animals can be abstracted into more elaborate and representative models (anchors) and/or simpler and more general models (templates) (after [75.17])

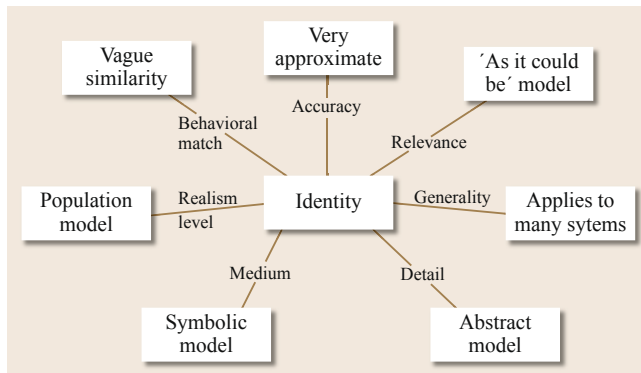


Fig. 75.5 Dimensions for describing models (after [75.18])

also influence how to structure bio-inspired robotics projects. After all, there is no correct model, but there are good or bad models with respect to the goal and hypothesis that are investigated. Webb has, for example, pointed out that there are seven major criteria with which we could evaluate models of bio-inspired robotics (Fig. 75.5 [75.18]):

1. Relevance to biology: as not all robotics research contributes to biological studies, it is important to clarify the degree to which a target robotic system and model are relevant.
2. Level: what are the base units of the model, and on what level of hierarchy in biological systems does the model attempt to represent?
3. Generality: a model could be developed for elucidating a mechanism of a specific system of interest, or for a more general mechanism that can be applied to many others. Therefore, the generality criterion considers how many systems the model intends to represent?
4. Abstraction: this criterion concerns the number and complexity of mechanisms included in the model.
5. Structural accuracy: there are many ways of representing systems but a question is the degree to which the model explains the internal mechanism of the target systems. In an extreme case, a model can behave the same at the level of input/output relationship, but it does not necessarily mean that the internal mechanism is the same.
6. Behavioral match: to what extent does the model behave like the target animal?
7. Medium of model: what is the model built from? A model can be made of mechanical, electrical, hydraulic, etc. or alternatively iconic, analog, symbolic, for example. Properly identifying these questions and the purpose of a robot is important. Indeed, there is a risk in bio-inspired robotics that a project is not useful to biology (i.e., it does

not properly address a scientific question) nor to robotics (i.e., it does not perform better than a more conventional robot).

75.2.3 Research Methods and Tools

As it might have been already noticed, robotics technologies are used for many different purposes in the context of bio-inspired robotics. Robots are often used to *explore* new research areas and questions; many platforms were built and examined for the purpose of *testing biological hypotheses*; some of the other platforms were developed specifically for *application discovery* based on the identified principles in biological studies; and more recently, robotics technologies were *interfaced with or integrated into biological systems* to understand or enhance animals capabilities.

Even though there are many successful contributions of robotics technologies to biological studies, it is often not trivial to identify what are the good methods and tools for the given specific hypothesis or problems. In particular, one of the most critical questions is probably whether it is necessary to build a physical robotic platform or it is sufficient to investigate pseudo-robots in simulation. Building physical robots is usually very costly and requires significant amount of additional knowledge and know how; thus there are many case studies of bio-inspired robotics research conducted only in simulation in the past [75.19, 20]. This type of research generally makes use of physics models or physically realistic simulation environments that allow us to explore fairly complex artificial creatures. This approach is useful to explore a large parameter space which cannot be optimized in the real-world platforms. Also, the use of virtual creatures in the bio-inspired robotics research is also extremely important to investigate concepts and hypotheses that are not possible to test technologically such as robots with point masses, frictionless joints, self-replication, and robotic hardware evolution that cannot be possible with our today's technologies.

However, building physical robots is a *must* in some cases. For example, there are often target concepts or hypotheses involved in physical processes that are difficult to theoretically model, such as friction, impacts, thermodynamics, and hydro/aerodynamics. In addition, there has been an increasing interest in complex robotic systems that contain a considerable number of physical elements such as joints and actuators, simulation models of which tend to be vulnerable against accumulated errors. Another aspect of robots used as a scientific tool is to explore hypotheses that cannot be tested in nature. This approach is often called synthetic methodology (an understanding-by-building approach [75.13]), meaning

that, by building and using artificial systems, we test biological principles that cannot be tested in conventional biological methods. The most representative example is the Braitenberg Vehicles, which we introduced in Sect. 75.1.1. Every vehicle has a set of oversimplified neural connections of an *animal* which does not exist in nature, but these creatures can explain important principles in biological systems. A similar approach was also

extended to the studies of *life as it could be* [75.21, 22], in which, by creating biological phenomena in simulation or robots, a broader and more universal understanding of living systems. This methodology is particularly effective in the studies related to evolutionary biology, in which verifications of hypotheses are usually very challenging ([75.20, 23]; see also the chapter of evolutionary robotics).

75.3 Case Studies

This section introduces three research areas that have been particularly active in bio-inspired robotics in the last few decades. Here we highlight the case studies in which robotics researches contributed to our further understanding of biological systems, and we illustrate how the concepts and methods we introduced in the previous sections were applied to these studies.

75.3.1 Bio-Inspired Legged Locomotion

Legged locomotion has been one of the most popular research topics in bio-inspired robotics for a long time because it characterizes the salient differences between biological and artificial systems. Although legged locomotion is seemingly easy, useful, and efficient for biological systems to move around in complex environments, it is surprisingly difficult to understand the underlying mechanisms hence challenging to implement into robotic systems. The legged locomotion research has a relatively long history that goes back to the foundation of biomechanics in the seventeenth century [75.24], and it became particularly popular when the modern robotics was established in the 1970s [75.25, 26]. One of the main reasons that many robotics researchers were attracted by the issue of legged locomotion lies in the fact that it covers many of the discrepancies between biological and artificial systems that we discussed in Sect. 75.2.1. More specifically, legged systems have to carry out many different tasks in unstructured environments such as establishing sturdy footholds, avoiding obstacles, dealing with variations of payload and velocities, and changing gait patterns, for example; Legged systems have to deal with massive parallel processes which are required for coordinating many joints and muscles, as well as local reflexes and high-level decision and planning; And adaptivity is essential for legged systems because they need to maintain mobility in different environments as well as under significant changes of its body plan over growth processes, for example. While there are countless case studies in the past, this subsection focuses on the four key challenges of bio-inspired

legged locomotion, i. e., stability, gait, energetics, and actuation, because they have been recognized as the long-standing challenges in bio-inspired legged locomotion. More comprehensive robotics research can be found in the section of legged locomotion.

Stability and Gait in Legged Locomotion

One of the main challenges in the study of legged locomotion is to uncover the mechanisms of motion stabilization against disturbances [75.27]. Biological systems usually make use of a variety of mechanisms including mechanical self-stabilization [75.28, 29], spinal reflexes [75.30, 31], central pattern generators [75.32], or sensory-motor control originated in the higher center of nervous system [75.33]. Because of the complexity of stabilization mechanisms in animals, bio-inspired robotics played an important role to systematically investigate the issues of stabilization through modeling of locomotion dynamics and reproducing the behaviors in legged robots of various kinds in the past.

Among others, bipedal walking was one of the most intensively studied topic areas which nicely illustrates how a synthetic approach could structure a research area of a complex biological problem. The backbone of this research area is the so-called *inverted pendulum walking model* which was originally investigated in biomechanics, and later used in the bio-inspired robotics research. The model considers the simplest physics representation of walking dynamics, i. e., a point mass is attached on a massless link, and simulates walking dynamics as the mass vaulting over the link [75.24]. This model can be, for example, physically implemented by the so-called rimless wheel that is the simplest *robotic* representation of the model (Fig. 75.6a; [75.34, 43]), and then, a slightly more complex configuration, the *compass gait model*, was proposed (Fig. 75.6b, [75.44];  VIDEO 111 shows an experiment of a compass gait bipedal robot locomotion on rough terrains). In contrast to the rimless wheel model that considers only stance leg dynamics during walking, the compass gait model has three masses with a passive hip joint, which allow us to investigate swing leg dynamics in addition to the stance

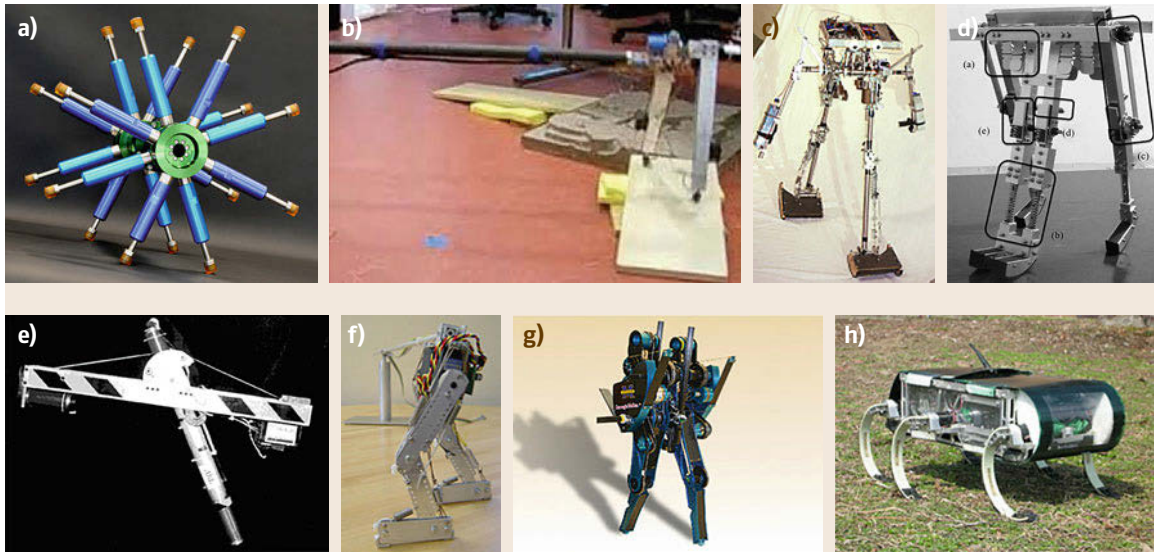


Fig.75.6a–h Examples of bio-inspired legged robots. (a) A physical implementation of rimless wheel walking model (after [75.34]), (b) A physical implementation of compass gait walking model (after [75.35, 36]), (c) passivity based bipedal walking robot (after [75.37]), (d) passive dynamic runner (after [75.38]), (e) energy efficient hopping robot (after [75.39]), (f) bipedal walking and running robot based on biarticular springs (after [75.40]), (g) biped robot based on variable stiffness actuators (after [75.41]), and (h) hexapod robot based on spring mass dynamics (after [75.42])

leg [75.45]. An important implication of this line of research lies in the fact that, because of the simple formulations of complex dynamics, researchers were able to systematically investigate different aspects of the complex behaviors while keeping an overarching structure of research issues. These simple models were, for example, gradually and systematically enhanced by integrating knee and ankle joints (Fig. 75.6c; [75.37, 43]), foot segments with variations of shapes, influences of mass distributions [75.46], influence of lateral motions, as well as a variety of advanced motion control architectures to demonstrate actuated locomotion in more complex environments [75.35, 36, 47, 48].

Although walking dynamics is a highly interesting challenge, the basic locomotion stability in walking is not sufficient to understand legged locomotion in nature, but stability has to be also maintained in different gait patterns, such as running because most of biological systems exhibit a rich variety of gaits. For this reason, running dynamics has also been studied intensively by investigating a simple model, i.e., the so-called spring-loaded inverted pendulum (SLIP model; [75.28, 49, 50]). The model consists of a point mass and a massless linear spring, on top of which many variations were proposed such as running models with nonlinear spring, segmented legs [75.51], swing leg dynamics, upper torso, lateral balancing [75.52], and wheel-like configuration (Fig. 75.6h [75.42]), for example. The SLIP model was also used to study walk-

ing dynamics and gait transitions between walking and running (Fig. 75.6f [75.40, 53]; VIDEO 110 shows an example of a biped robot walking and running). It is important to note that many of these models and robots were developed for the hypotheses difficult to test in biological systems. The biological legs are hardly linear springs but they consist of numerous active and nonlinear components. However, by examining these models and robots, we are able to learn the basic underlying principles such as the degree to which a spring-like behavior of legs could contribute to the stability of walking and running locomotion, for example. In addition, such an abstraction of biological body structures is very practical for robotics research as we are able to design and construct robots based on the underlying principles without replicating complex anatomical structures consisting of organic components.

Energy Efficiency and Bio-Inspired Actuation

Another considerable challenge in the study of bio-inspired legged locomotion is the principles for energy efficiency. It has been known that the locomotion efficiency of biological systems is known to be at least an order of magnitude better than most of the legged robots today but it is not fully understood why biological locomotion is so efficient. The complexity of the energetic problem in legged locomotion is originated in the many possible sources of energy dissipation such as frictional and damping losses in joints and mus-

cles, mechanical impact losses at foot touchdown to the ground, metabolic costs, and energy required for acceleration and deceleration of body parts. Because of such a complexity, the bio-inspired robotics research has been significantly contributing to this problem by building and analyzing, for example, purely mechanical locomotion systems [75.38, 43], underactuated locomotion control [75.35, 37], the use of passive spring and self-excited vibration [75.39, 54], and exoskeleton devices [75.55]. All of these case studies were contributing to a comprehensive understanding of energy efficiency in biological locomotion [75.56], and some of the hypotheses have been analyzed and tested in biological systems.

In addition to the whole body dynamics, energy efficient locomotion has also been investigated at the level of actuation because the muscle-tendon systems play a major role in animals' efficient locomotion. Inspired from the biological models of muscles, this research trend started from the so-called series elastic actuators, which is an actuator unit containing a mechanical spring

being installed in series to an electric motor [75.62]. The implementation of mechanical spring in an electric motor explained the unique characteristics such as storage of kinetic energy to elastic energy, shock absorption to protect mechanical transmission, and force-based feedback control, all of which are favorable for both biological and artificial legged systems. More recently, many researchers have been attempting to enhance the actuation mechanisms with variable stiffness and damping capabilities [75.41, 63] that are also expected to provide valuable insights into the roles of muscle properties in efficient legged locomotion.

75.3.2 Reflexes and Central Pattern Generators

Agility and adaptability of animals' locomotion are not only originated in mechanical dynamics as explained in the previous subsection, but there are also highly complex control systems regulating animals' motions. Usually animals control systems are labeled into four

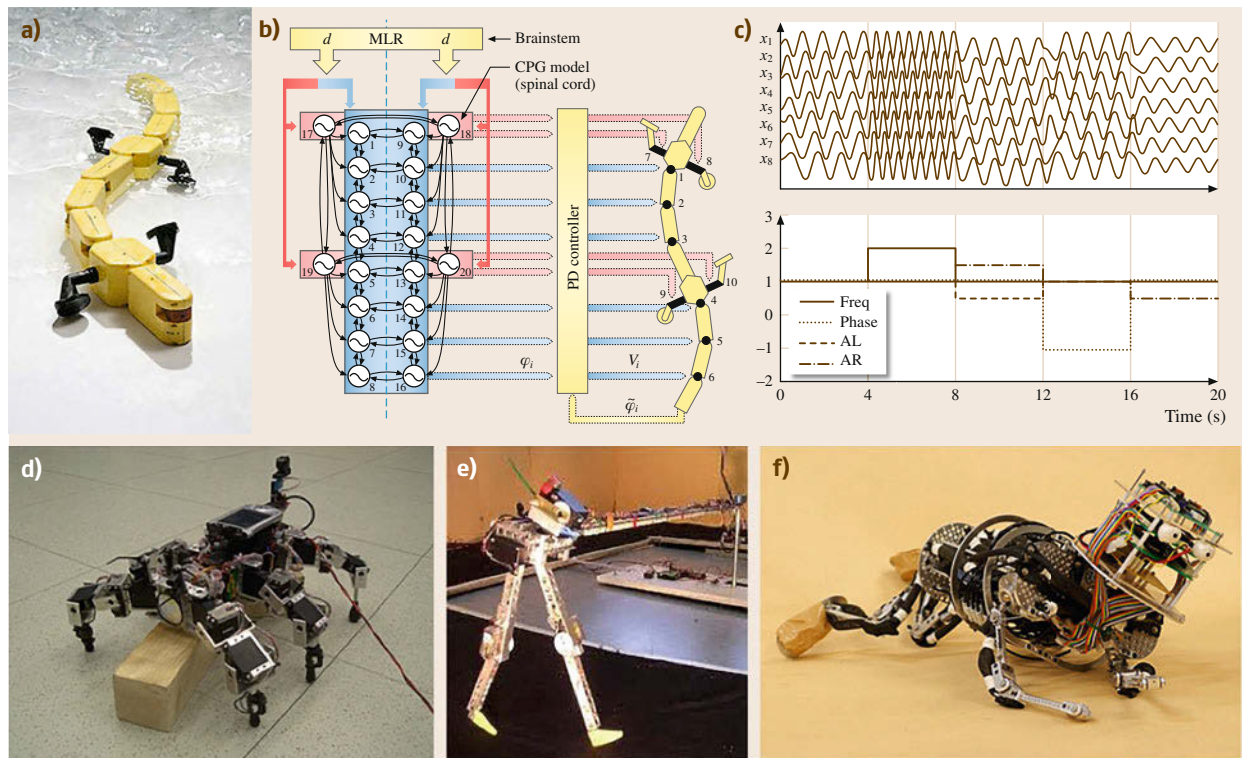


Fig. 75.7a–f Robotic implementation of CPG models. (a) A salamander robot consisting of motorized modules, and (b) its control architecture. Every module has a servomotor which is controlled through a simulated CPG model. (c) Typical behavioral response of the CPG model (upper figure) with respect to a control signal (lower figure). One control input is sufficient to control smooth oscillations of multiple body segments because of coupled dynamics originated in the CPG model (after [75.57]). (d, e) A hexapod and biped robots that use CPG models to adapt to changes in the environment (after [75.58–60]). (f) A musculoskeletal humanoid robot that simulate developmental processes of human babies (after [75.61])

components: the musculoskeletal system, reflexes, central pattern generators (CPGs), and modulation by higher control centers. Bio-inspired robotics has been investigating these components individually or in combination, and resulted in a number of demonstrations of surprisingly robust robot locomotion (Fig. 75.7).

This research area has been historically investigated by the two distinguished approaches, i.e., the CPG-based approach and the reflex-based one. The former approach usually considers voluntary oscillations of neural circuits, that is, CPGs, and the output of these circuits triggers locomotion cycles. Because these behaviors are found in the spinal cord of vertebrate animals and in ganglions in invertebrates [75.64], this approach has been very popular in the bio-inspired robotics. In contrast, the reflex-based approach does not incorporate intrinsic oscillators and generate periodic behavior as a chain of reflex-mediated events. While conceptually different, most of the CPG-based approach considers reflexes in the neural processes; thus these two approaches are often overlapping and reflex-based approaches can be seen as a subset of CPG-based approaches.

One of the pioneering works in the reflex-based approach was based on the neural circuits underlying walking identified in stick insects [75.65, 66]. In this study, it was identified that a series of reflexes for each leg use information related to leg postures and ground contact to generate movements. Coordination between legs (i.e., specific gaits) is obtained with direct neural couplings between individual legs circuits and also through mechanical couplings (e.g., the movement of one limb affecting the load on other limbs). This leads to a decentralized control mechanism, similar in spirit to those developed in behavior-based robotics, that has been validated on simulated and real hexapod robots [75.65, 67].

The reflex-based approach was also investigated in human walking, in which a series of neuromechanical models were developed to demonstrate how the combination of muscle properties and low-level reflexes can lead to stable locomotion in simulated bipeds [75.68, 69]. In particular, Geyer and Herr [75.69] present a simulated bipedal walker which manages to walk in the sagittal plane and to be stable against slight slopes. This model captures principles of neuromuscular feedbacks and predicts muscle activation patterns observed in leg muscles. Similar reflex-based controllers (without muscle models but with simulated synaptic plasticity) have successfully been ported to real robots such as the Runbot [75.60] and the dynamic walkers reported in [75.37].

One of the first examples of the CPG approach has been done in simulation by Taga and colleagues [75.70, 71]. They developed a series of 2-D models of biped locomotion that combine a simple musculoskeletal

model with a CPG modeled as a system of coupled *Matsuoka* oscillators [75.72]. The work showed how bidirectional couplings between the CPG and the musculoskeletal model could lead to entrainment (i.e., frequency locked regimes) between the two as well as to robust locomotion. Since then a large number of CPG-based controllers have been implemented in robots for different types of locomotion. Examples include hexapod and octopod robots [75.73–75] (see also Robot Roach  VIDEO 112), swimming robots [75.76–78] (see also Salamandra Robotica  VIDEO 113), quadruped robots [75.57, 79, 80], and biped robots [75.81–85].

As discussed in [75.64], a CPG-based approach has several interesting properties:

- i) Stable limit cycle behavior that provides robustness against perturbations.
- ii) Suitability for a distributed implementation.
- iii) Possibility to modulate gaits with a few control parameters.
- iv) Integration of sensory feedback signals in order to obtain mutual entrainment between the CPG and the mechanical body.
- v) Suitable substrate for learning and optimization algorithms. These properties were particularly difficult to investigate by using animals; hence the bio-inspired robotics has provided significant contributions to the nature of motion control in biological systems.

75.3.3 Bio-Inspired Navigation

Biological systems use a variety of cognitive processes for their navigation in complex environment: it is known, for example, that animals use both proprioceptive and exteroceptive receptors for sensing environments; the obtained sensory information is passed to massively parallel processes distributed over many hierarchical levels in central nervous systems; animals' perception of the world is coordinated with low-level sensory-motor processes; and in addition to these mechanisms, long-term planning and learning processes are continuously running to achieve more advanced tasks such as goal-directed navigation. In order to tackle such a complex problem of animals' navigation, bio-inspired robotics also provided a set of effective tools to apply the synthetic methodology some of which are outlined in this subsection.

Sensor Morphology and Sensory-Motor Coordination

A significant number of researchers in bio-inspired robotics have been working on relatively simple animals

such as insects because their central nervous systems are far more tractable than other animals. Despite the simplicity of their brains, insects are incredible navigators being capable of avoiding obstacles while running or flying with enormous speed, recognizing landmarks in unstructured environment, and traveling long distance for foraging. Moreover, some of the social insects can even learn to go back to their own nests, and communicate with co-workers for efficient *community management*. Although biologists have been investigating these fascinating animals for centuries, there are still a number of issues that are not fully clarified yet, and among others, robotics platforms were used to investigate the mechanisms in which physical system–environment interactions play central roles [75.86].

One of the most successful case studies in bio-inspired navigation research was on the mechanisms of sensory-motor coordination in flying insects such as flies and bees. These insects are known to rely on visual sensory information, more specifically, optic flow to detect ego motions, stabilize body posture, measure distance to various objects and landing spots, and track traveling distance, for example. While the visual information processing is usually regarded as computationally expensive, many insects, which have very limited computational resources, make use of this modality to achieve these behavioral functions. The underlying mechanisms are found in the *hardware setups* of animals, in which sensor morphology (i.e., how receptors are distributed) and low-level sensory information processing are exploited in the coordination of sensory-motor processes [75.87]. More specifically, the photoreceptors of these insects are usually distributed to almost all directions which give rise to surprisingly informative stimuli about the environment and ego motions, and low-level neural circuits are configured such that extremely low-processing power is necessary. To test these hypotheses, a number of robotic platforms were developed and tested previously, which showed the feasibility of these mechanisms such as the optic flow to detect nearby objects [75.88], visual odometry [75.89], flight altitude [75.90], and flight stabilization [75.91].

Technological advances are essential to gain additional insights into the complex sensory-motor processes in the animals. At the beginning of the investigations, many researchers developed omni-directional vision based on specifically shaped mirrors attached to regular cameras, while recently more advanced technologies are being developed to flexibly adjust photoreceptors [75.92]. Neuromorphic engineering also provides an additional enabling technology to explore physical foundations of biological nervous systems [75.93, 94]. Neuromorphic silicon retinas are, unlike conventional visual sensors, able to process sensory

information extremely fast and computationally less demanding owing to the event driven and asynchronous processing architectures, while keeping sensitivity very high (i.e., the receptors can be sensitive in very dark environments as well as in a very bright one, [75.95]). With the technological progress, we will be able to reproduce more precise landscape of the world from insects' viewpoint for more comprehensive investigation of bio-inspired navigation.

Goal-Directed Navigation

Compared to reflexive behaviors, goal-directed ones are significantly more complex where much less is known even in biology. In nature, goal-directed behaviors such as navigation to a nest from a distant location require learning of routes and locations, short- and long-term memories, episodic memories, while flexibly adapting to unstructured and often dynamically changing environments. The underlying mechanisms are related to many different locations in the central nervous systems and they vary one species to another, thus the ongoing researches are essentially driven on the basis of the important findings in biology, rather than developing a unified and generalized framework.

One of the representative case studies on bio-inspired goal-directed navigation was again conducted in relation to insect behaviors (Fig. 75.8): some social insects such as desert ant *Cataglyphis* are known to exhibit the so-called *visual homing* behaviors, in which the animals go back to their nests by using visual cues nearby [75.96]. These insects usually walk randomly when searching for food sources, while they go back straight to the nest by using visual cues. Although the neural basis of these behaviors is not yet identified, the biologists argue that an abstract model, the so-called *average landmark vector* method, explain the insects' behavior fairly accurately. Here it is assumed that insects know the global orientation in the world, and every once in a while, they perceive the direction of foraging behavior stored as vector information. Over time, the animals sum up the vectors so that they can keep track on the direction to the nest while randomly search for the food sources. The biologists have been exploring these behaviors for decades, and the accumulated knowledge and hypothetical models were implemented and tested in physical robot platforms. Unlike most of the simulation experiments, the implementation to the robots helped to test the hypothesis in the real-world desert environment [75.96], or physically implemented in an analog circuitry (see also multimedia material of Analog Robot navigation in  VIDEO 242 ; [75.97]).

A significantly more challenging problem is to identify the mechanisms of goal-directed behaviors in more complex animals, especially in mammals. There

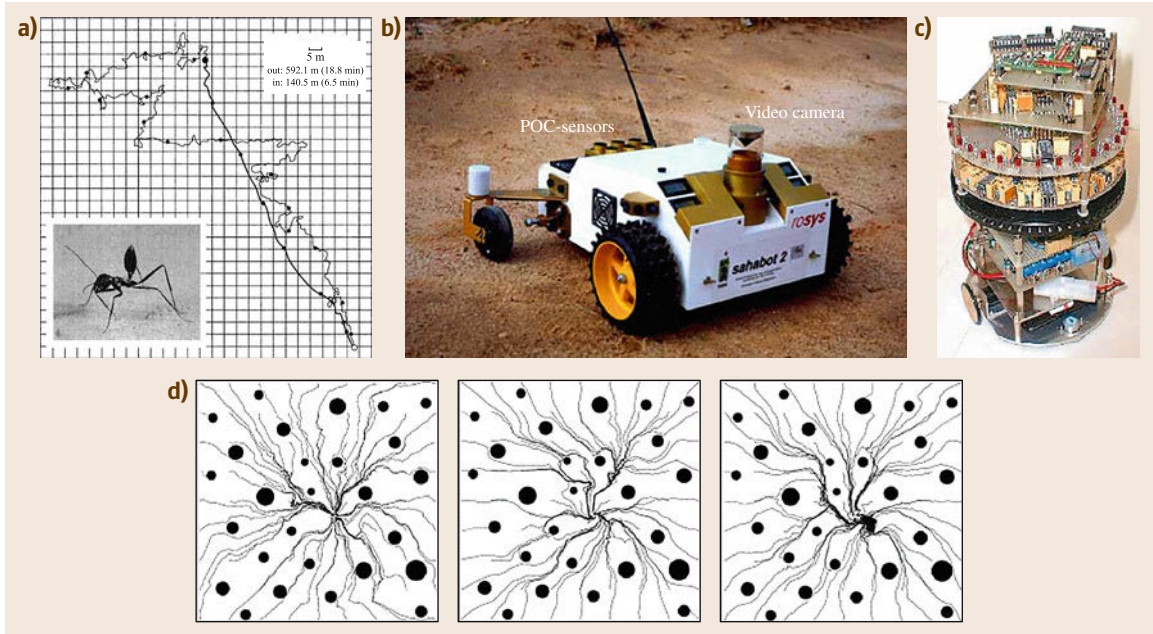


Fig.75.8a–d Visual homing of insect-inspired robots. **(a)** An result of navigation experiment of desert ant *Cataglyphis*. **(b)** A mobile robot Sahabot II that was developed to investigate navigation mechanisms of *Cataglyphis*. The robot is equipped with an omni-directional camera and a digital compass that can be used for the bio-inspired landmark navigation (after [75.96]). **(c)** A fully analog implementation of the visual homing algorithm. **(d)** Simulation results of visual homing algorithm (after [75.97])

is a large body of literature about this issue including cognitive science and brain science, but one of the most prominent contributions of robotic platforms in this research area was to explore neural dynamics during physical system–environment interactions. The research was originally motivated by a discovery in physiology such as the so-called place cells, i. e., a group of neurons in hippocampus exhibit unique behaviors whenever the animal is in a specific location in an environment [75.98]. This hard evidence in neuroscience has been widely used to analyze how brains function in the context of spatial cognition and navigation

in general, including those investigating computational neuroscience and bio-inspired robotics. Essentially, it is still a challenge to explain the behaviors of place cells because they involve sensory-motor activities as well as temporal changes of neural activities (i. e., learning of sensory motor activities) thus a synthetic methodology is extremely helpful. So far it has been shown that the computational models of hippocampus were implemented onto some mobile robot platforms to replicate the behaviors of place cells in navigation tasks [75.99, 100] as well as some more complex goal-oriented behaviors and learning [75.101].

75.4 Landscape of Bio-Inspired Robotics Research and Challenges

So far we introduced only a few representative and ongoing case studies of bio-inspired robotics research, but there are many other active topic areas in the field. Although many of these studies are covered also in the other chapters of this handbook, this section provides a brief overview of the relevant topics in which robotic technologies are being used as scientific tools for biology.

75.4.1 Bio-Inspired Climbing

When legged systems are reduced down to smaller scales, adhesion forces become more dominant than the gravitational, and for this reason, the small-sized animals in nature such as insects, amphibians, and lizards tend to climb terrains rather than walk on level grounds. While the governing physics in the climbing

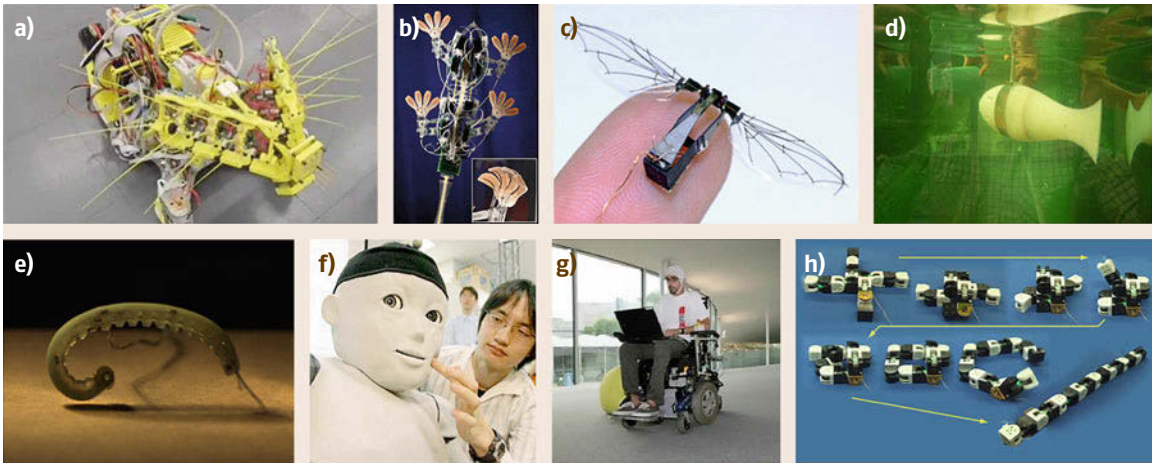


Fig.75.9a–h Examples of recent bio-inspired robots. **(a)** A mobile robot that uses active whisker arrays for navigation (after [75.102]). **(b)** A climbing robot based on feet made of dry adhesives (after [75.103]). **(c)** Micro robot for flapping flight developed by the micro-fabrication techniques (after [75.104]). **(d)** A fish-like swimming robot that exploits soft continuum body structure (after [75.105]). **(e)** A worm-like robot that exhibit rolling-locomotion of soft body structure (after [75.106]). **(f)** A humanoid robot that is equipped with soft skin for interactions with human partners (after [75.107]). **(g)** A wheel-chair controlled by brain signals of the user (after [75.108]). **(h)** Self-reconfigurable robot that is capable of autonomously changing its own body structure (after [75.109])

locomotion is different from that of gravity-oriented legged locomotion, robotic platforms are also useful because the dynamics during the locomotion is similarly complex. One of the most representative case studies in this line of research was the use of dry adhesives in climbing robots that are inspired from geckos. Many research topics focused on the fabrication techniques of micro hair-like structures that can generate adhesive forces for a series of small-sized robots (Fig. 75.9b, [75.103, 110]). Similarly a few other approaches were also proposed to explore the different climbing strategies of animals including the use of material-dependent adhesion [75.111], rough-surface locomotion by using feet with micro spine structures [75.112, 113], and climbing strategy based on force closure of relatively long legs [75.114]. There still exist many challenges in fabrication techniques of micro structures in order to replicate the sophisticated climbing mechanisms of animals, which requires continuing close collaborations between researchers in biology and robotics.

75.4.2 Flapping Flight and Swimming Mechanisms

Another complex, yet popular, dynamics used in animal kingdom is fluid/aerodynamics that are typically observed in flying and swimming systems. Fluid/aerodynamics are also dynamics difficult to model and simulate thus robotic platforms are intensively em-

ployed for exploring underlying mechanisms [75.115, 116]. As is the case of walking and running on land, mechanical dynamics also play an important role in flying and swimming locomotion and a number of underactuated robots were developed to understand the nature of locomotion in fluid Fig. 75.9d [75.105, 117]. As the microfabrication techniques evolved in the recent years, roboticists and biologists also started collaborating to investigate small-sized flying robots (Fig. 75.9c, [75.104]; Chap. 26).

75.4.3 Artificial Hands, Haptics, and Whiskers

Haptic perception is known to be one of the most important sensor modalities in biological systems, although the biological nature is far from a comprehensive understanding because animals make use of complex sensory-motor interactions for the purpose of tactile sensing [75.118, 119]. Haptic sensing can be defined as sensing of mechanical environment through *touch* although there are many different variations in nature including tactile sensing through fingers and skins [75.119], active whisking (Fig. 75.9a) [75.102], or more specifically targeted sensing such as slippage detection [75.120]. Exploration on haptic technologies is also crucial in this research area as the biological tactile sensing involves an enormous number of mechanoreceptors each of which has a large sensitivity range. Currently, a number of researchers are actively inves-

tigating technological solutions through haptic devices and soft and stretchable electronics for tactile sensing [75.121, 122].

75.4.4 Self-Reconfigurable and Evolutionary Robotics

Animals' adaptivity in nature relies significantly on their capability of changing their body sizes and structures. Animals are, for example, able to start their lives smaller and gradually grow larger and more complex; they are able to self-repair or regenerate when encountering failures in body parts; and muscles and skins are able to strengthen themselves if necessary [75.123]. Synthetic methodology has also been employed to investigate these fascinating capabilities of biological systems by using, for example, modular robots Fig. 75.9h [75.109, 124, 125], redundant body structures for snake-like motion control [75.126, 127], and self-repair and self-assembly of structures [75.128, 129]. Due to the technological limitations, many researchers take advantage of simulation-based methods to explore the ontogenetic and evolutionary processes to uncover the characteristics of optimization strategies in nature [75.19, 20, 130].

75.4.5 Bio-Inspired Soft Robots

Unlike the conventional robots that are usually made of rigid materials articulated into discrete pieces, animals' body structures mostly consist of soft, continuum,

and elastic components such as muscles, tendons, skins, organs surrounded by smooth membrane [75.1]. Recently, there has been an increasing interest in the use of soft deformable materials in robotic systems to enhance capabilities of, for example, soft locomotion [75.106, 131] ( VIDEO 109 shows an example of soft robot locomotion), manipulation [75.132, 133], shape adaptation [75.134], and soft human–robot interactions [75.63]. Despite its demand in the robotics and biological studies, there are still a number of technological challenges in this field such as soft actuation and sensing [75.135], simulation of soft deformable structures [75.136], and control of flexible continuum bodies [75.137].

75.4.6 Neuroprosthetics and Social Interactions

As we develop more technological components compatible to biological systems, there are more possibilities to implant artificial devices into biological bodies. Although most of the case studies in this research area aim at bio-medical applications as exemplified by visual/auditory prosthetics, pain relief, and motor prosthetics, there are also intensive investigations on the use of prosthetic devices to gain additional insights into the nature of motion control [75.108, 138] and perception [75.139]. There is also an increasing interest in the use of robotic platforms in the studies of social interactions where robots are used to study communications with humans [75.107] and the other animals [75.140].

75.5 Conclusion

This chapter introduced a class of bio-inspired robotics research that is specifically targeted to deepen our understanding of biological systems. Through the representative case studies, we explained how bio-inspired robotics research can be useful not only for developing innovative robots, but also for exploring uncovered challenges in biology by employing the understanding-by-building approach. There are, however, a set of important concepts that need to be considered for successful collaborations between robotics and biology. Specifically:

1. It is necessary to take the similarities and differences in robots and animals into account.
2. There are different goals and methods to develop models of biological systems.
3. The use of robots as a scientific tool has both advantages and disadvantages.
4. There are types of hypotheses in biology that bio-inspired robotics can be particularly beneficial for.

And finally, we also introduced a concise landscape of trends and challenges in bio-inspired robotics. As mentioned earlier, the field of bio-inspired robotics is very broad, and the outline introduced in this chapter is by no means complete. For example, although this chapter only focused on the types of research which contribute to biological studies, there is a large body of the literature on *bio-inspired robotic applications* which are mostly ignored in this chapter. The interested readers should refer to the other chapters in this handbook as well as the other review articles in the field. Also, there are significantly more case studies available in literature which reported on the different species or the other aspects of animals which were summarized in [75.15, 18, 64].

Video-References

-  **VIDEO 109** Dynamic rolling locomotion of GoQBot
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/109>
-  **VIDEO 110** JenaWalker – Biped robot with biologically-inspired bi-articular springs
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/110>
-  **VIDEO 111** MIT Compass Gait Robot – Locomotion over rough terrain
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/111>
-  **VIDEO 112** RobotRoach with adaptive gait pattern variations
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/112>
-  **VIDEO 113** Salamandra Robotica II – Swimming to walking transition
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/113>
-  **VIDEO 242** Analog Robot
available from <http://handbookofrobotics.org/view-chapter/75/videodetails/242>

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76. Evolutionary Robotics

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Evolutionary Robotics is a method for automatically generating artificial brains and morphologies of autonomous robots. This approach is useful both for investigating the design space of robotic applications and for testing scientific hypotheses of biological mechanisms and processes. In this chapter we provide an overview of methods and results of Evolutionary Robotics with robots of different shapes, dimensions, and operation features. We consider both simulated and physical robots with special consideration to the transfer between the two worlds.

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Evolutionary robotics is a method for the automatic creation of autonomous robots [76.1]. It is inspired by the Darwinian principle of selective reproduction of the fittest, captured by evolutionary algorithms [76.2]. In evolutionary robotics, robots are considered as autonomous artificial organisms that develop their own control system and body configuration in close interaction with the environment without human intervention. Drawing inspiration from principles of biological self-organization, evolutionary robotics includes elements

of evolutionary, neural, developmental, and morphological systems. The idea that an evolutionary process could drive the generation of control systems dates back to at least the 1950s [76.3] with a more explicit form appearing in the mid 1980s with the ingenious thought experiments by neuroscientist *Valentino Braitenberg* on neurally driven vehicles [76.4]. In the early 1990s, the first generation of simulated artificial organisms with a genetic code describing the neural circuitry and morphology of a sensory motor system began evol-

ing on computer screens [76.5–8]. At that time, real robots were still complicated and expensive machines that required specialized programming techniques and skillful manipulation. Towards the end of that period, a new generation of robots started to emerge that shared important characteristics with simple biological systems: robustness, simplicity, small size, flexibility, and modularity [76.9,10]. Above all, those robots were

designed so that they could be programmed and manipulated by people without engineering training. Those technological achievements, together with the growing influence of biological inspiration in artificial intelligence [76.11], coincided with the first evolutionary experiments on real robots [76.12–14] (👁 VIDEO 39 and 👁 VIDEO 371), and the term evolutionary robotics was coined [76.15].

76.1 Method

The major methodological steps in evolutionary robotics proceed as follows (Fig. 76.1). An initial population of different artificial chromosomes, each encoding the control system (and possibly the morphology) of a robot, is randomly created. Each of

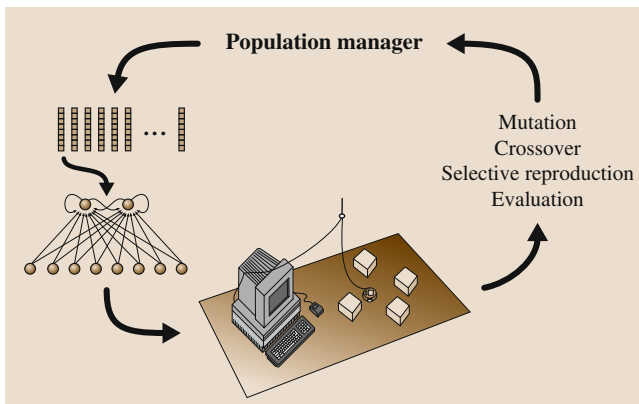


Fig. 76.1 Evolutionary experiments on a single robot. Each individual of the population is decoded into a corresponding neurocontroller which reads sensory information and sends motor commands to the robot every 300 ms while its fitness is automatically evaluated and stored away for reproductive selection

these chromosomes is then decoded into a corresponding controller, for example a neural network (NN), and downloaded into the processor of the robot. The robot is then let free to act (move, look around, manipulate the environment) according to a genetically specified controller while its performance for a given task is automatically evaluated. Performance evaluation is done by a fitness function that measures how fast and straight the robot moves, how frequently it collides with obstacles, etc. This procedure is repeated for all chromosomes of the population. The fittest individuals (those that have received more fitness points) are allowed to reproduce by generating copies of their chromosomes with the addition of random modifications introduced by genetic operators (e.g., mutations and exchange of genetic material). The newly obtained population is then tested again on the same robot. This process is repeated for a number of generations until an individual is born which satisfies the fitness function set by the user. The control system of evolved robots, encoded in an artificial genome, is therefore generated by a repeated process of selective reproduction, random mutation, and genetic recombination, similarly to what happens in natural evolution (👁 VIDEO 119).

76.2 First Steps

In an early experiment on robot evolution without human intervention, carried out at Ecole Polytechnique Fédérale de Lausanne (EPFL) [76.12], a small wheeled robot was evolved for navigation in a looping maze (Fig. 76.2). The Khepera robot has a diameter of 55 mm and two wheels with controllable velocities in both directions of rotation. It also has eight infrared sensors, six on one side and two on the other side, that can function either in active mode to measure distance from obstacles or in passive mode to measure the amount of (infrared) light in the environment. The robot was con-

nected to a desktop computer through rotating contacts that provided both power supply and data exchange through a serial port (👁 VIDEO 39).

A simple genetic algorithm [76.16] was used to evolve the synaptic strengths of a neural network composed of eight sensory neurons and two motor neurons. Each sensory unit was clamped to one of the eight active infrared sensors whose value was updated every 300 ms. Each motor unit received weighted signals from the sensory units and from the other motor unit, plus a recurrent connection with itself with a 300 ms

delay. The net input of the motor units was offset by a modifiable threshold and passed through a logistic squashing function. The resulting outputs, in the range $[0, 1]$, were used to control the two motors so that an output of 1 generated maximum rotation speed in one direction, an output of 0 generated maximum rotation speed in the opposite direction, and an output of 0.5 did not generate any motion in the corresponding wheel. A population of 80 individuals, each coding the synaptic strengths and threshold values of the neural controllers, was initialized with all weights set to small random values centered around zero. Each individual was tested on the physical robot for 80 sensorimotor cycles (approximately 24 s) and evaluated at every cycle according to a fitness function with three components measured onboard the robot

$$\phi = V(1 - \sqrt{\Delta v})(1 - i), \quad (76.1)$$

where V is the average rotation speed of the two wheels, Δv is the absolute value of the algebraic difference between the signed speed values of the wheels (positive is one direction, negative the other), and i is the normalized activation value of the infrared sensor with the highest activity. The first component is maximized by speed, the second by straight motion, and the third by distance from objects.

During the first 100 generations, both average and best fitness values grew steadily, as shown in Fig. 76.3. A fitness value of 1.0 would correspond to a robot moving straight at maximum speed in an open space and therefore was not attainable in the looping maze shown in Fig. 76.2, where some of the sensors were often active and where several turns were necessary to navigate. Fig. 76.4 shows the trajectory of the best individual of the last generation.

Although the fitness function did not specify in what direction the robot should navigate (given that it

was perfectly circular and that the wheels could rotate in both directions), after a few generations all the best individuals moved in the direction corresponding to the side with the highest number of sensors. Individuals moving in the other direction had a higher probability of colliding into corners without detecting them and thus disappeared from the population. Furthermore, the cruising speed of the best evolved robots was approximately half of the maximum speed that could be technically achieved and did not increase even when the evolutionary experiment was continued up to 200 generations. Further analysis revealed that this self-limitation of the navigation speed had an adaptive function because, considering the sensory and motor

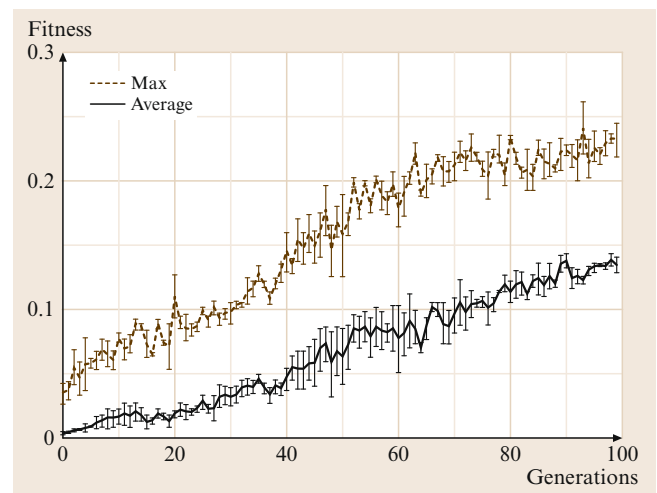


Fig. 76.3 Average fitness of the population and fitness of the best individual at each generation (error bars show standard error over three runs from different initial populations)

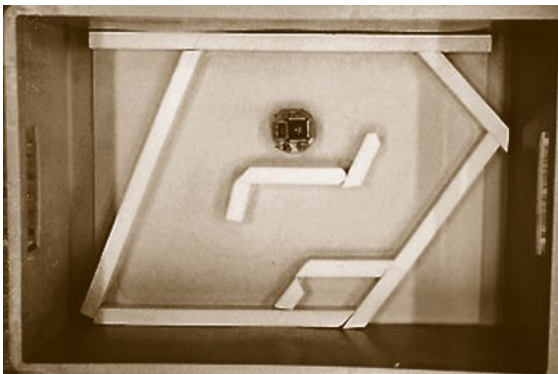


Fig. 76.2 Bird's-eye view of the desktop Khepera robot in the looping maze

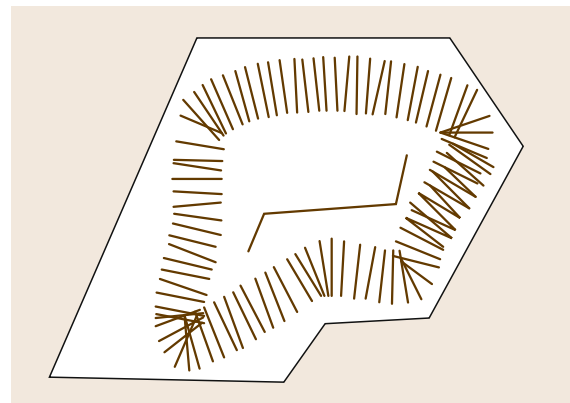


Fig. 76.4 Trajectory of the robot with the best neural controller of the last generation. Segments represent the axis between the two wheels. Data were recorded and plotted every 300 ms using an external laser positioning device

refresh rate together with the response profile of the distance sensors, robots that traveled faster had a higher risk of colliding with walls before detecting them; they gradually disappeared from the population.

Despite its simplicity, this experiments shows that evolution can discover solutions that match not only the computational requirements of the task to be solved, but also the morphological and mechanical properties of the robot in relation to its physical environment.

76.2.1 Evolution of Neural Controllers for Walking

Over the past 20 years or so, there has been a growing body of work on evolving controllers for various kinds of walking robots – a nontrivial sensorimotor coordination task. Early work in this area concentrated on evolving dynamical network controllers for simple (abstract) simulated insects (often inspired by cockroach studies) which were required to walk in simple environments [76.17, 18]. Earlier, *Beer* et al. had introduced a neural architecture for locomotion based on studies of cockroaches [76.19], which is shown in Fig. 76.5. The promise of this work soon led to versions of this methodology being used on real robots. Probably the first success in this direction was by *Lewis* et al. [76.14, 20] who evolved a neural controller for a simple hexapod robot using coupled oscillators built from continuous-time, leaky-integrator, artificial neurons. All evaluations were done on the actual robot with each leg connected to its own pair of coupled neurons, leg swing being driven by one neuron and leg elevation by the other. These pairs of neurons were cross connected, in a manner similar to that used by *Beer* and *Gallagher* [76.18] (Fig. 76.5), to allow coordination between the legs. In order to speed up the process, they employed staged evolution where first an oscillator capable of moving a leg was evolved and then an architecture based on these oscillators was further evolved to develop walking. The robot was able to execute an efficient tripod gait on flat surfaces.

Gallagher et al. [76.21] described experiments where neural networks controlling locomotion in an artificial insect were evolved in simulation and then successfully downloaded onto a real hexapod robot. This machine was more complex than *Lewis* et al.'s, with a greater number of degrees of freedom per leg. In this approach, each leg was controlled by a fully connected network of five continuous-time, leaky-integrator neurons, each receiving a weighted sensory input from that leg's angle sensor. Initially the architecture shown in Fig. 76.5 was used, with the connection weights and neuron time constants and biases under genetic control. This produced efficient tripod gaits for walking on flat

surfaces. In order to produce a wider range of gaits operating at a number of speeds such that rougher terrain could be successfully negotiated, a different distributed architecture, more inspired by stick insect studies, was found to be more effective [76.22].

Galt et al. [76.23] used a genetic algorithm to derive the optimal gait parameters for a Robug III robot, an eight-legged, pneumatically powered walking and climbing robot. The individual genotypes represented parameters defining each leg's support period and the timing relationships between leg movements. These parameters were used as inputs to a mechanistic finite-state machine pattern-generating algorithm that drove the locomotion. Such algorithms, which are often used in conventional walking machines, rely on relatively simple control dynamics and do not have the same potential for the kind of sophisticated multigait coordination that complex dynamical neural network archi-

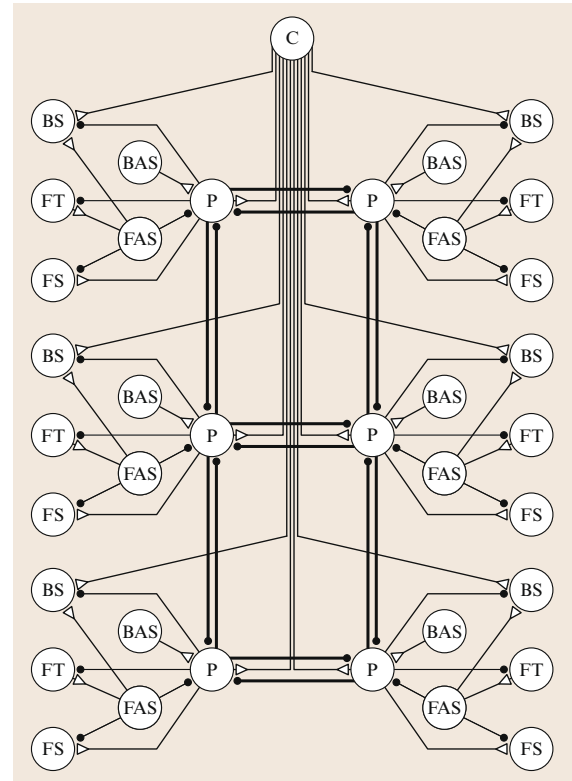


Fig. 76.5 Schematic diagram of a distributed neural network for the control of locomotion as used by *Beer* et al. [76.19]. Excitatory connections are denoted by open triangles and inhibitory connections are denoted by filled circles. C, command neuron; P, pacemaker neuron; FT, foot motor neuron; FS and BS, forward swing and backward swing motor neurons; FAS and BAS, forward and backward angle sensors

tures, such as those described in this section, have been shown to produce. However, controllers were successfully evolved for a wide range of environments and to cope with damage and systems failure (although an individual controller had to be tuned to each environment; they were not able to self-adapt across a wide range of conditions). Gomi and Ide [76.24] evolved the gaits of an eight-legged robot (Fig. 76.6) using genotypes made of eight similarly organized sets of genes, each gene coding for leg motion characteristics such as the amount of delay after which the leg begins to move, the direction of the leg's motion, the end positions of both vertical and horizontal swings of the leg, and the vertical and horizontal angular speed of the leg. After a few dozen generations, where evaluation was on the robot, a mixture of tetrapod and wave gaits was obtained. Using the cellular encoding [76.25] developmental approach – which genetically encodes a grammar-tree program that controls the division of cells growing into a dynamical recurrent neural network of the kind used by Beer et al. – Gruau and Quatramaran [76.26] evolved a single-leg neural controller for the same eight-legged robot used by Gomi and Ide. This generated a smooth and fast quadrupod locomotion gait (📺 VIDEO 372 and 📺 VIDEO 373). Kodjabachian and Meyer [76.27] extended this work to develop more sophisticated locomotion behaviors. Jakobi [76.28] successfully used his minimal simulation techniques (described in Sect. 76.3) to evolve controllers for the same eight-legged robot as Gruau. Evolution in simulation took less than 2 h on what would today be regarded as a very slow computer, and was then successfully transferred to the real robot. Jakobi evolved modular controllers based on Beer's continuous recurrent networks to control the robot as it engaged in walking about its environment, avoiding obstacles and seeking out goals depending on the sensory input. The robot could smoothly change gait, move backward and forward, and even turn on the spot. More recent work has used similar architectures to those explored by the researchers mentioned above, to control more mechanically sophisticated robots such as the Sony Aibo [76.29].

Recently there has been successful work on evolving coupled oscillator style neural controllers for the highly unstable dynamic problem of biped walking. Reil and Husbands [76.30] showed that accurate physics based simulations employing physics-engine software could be used to develop controllers able to generate successful bipedal gaits (📺 VIDEO 374). Reil et al. have now significantly developed this technology to exploits its commercial possibilities, in the animation and games industries, for the real-time control of physically simulated three-dimensional (3-D)

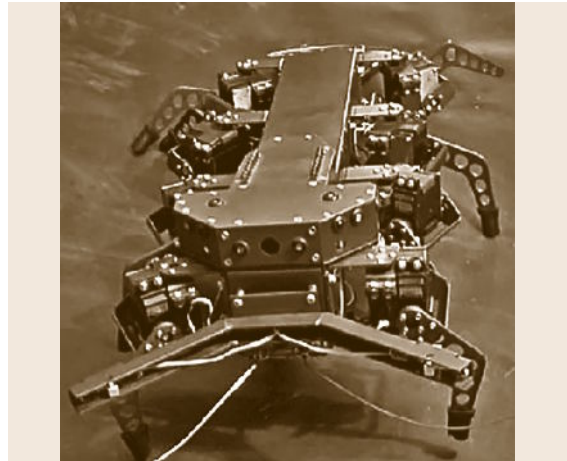


Fig. 76.6 The octopod robot built by Applied AI Systems Inc.

humanoid characters engaged in a variety of motor behaviors (refer to [76.31] for further details). Coupled neural oscillators have been evolved also to control the swimming pattern of articulated, snake-like, underwater robots using physics-based simulations [76.32].

Vaughan has taken related work in another direction. He has successfully applied evolutionary robotics techniques to evolve a simulation of a 3-D ten-degree-of-freedom bipedal robot. This machine demonstrates many of the properties of human locomotion. By using passive dynamics and compliant tendons, it conserves energy while walking on a flat surface. Its speed and gait can be dynamically adjusted and it is capable of adapting to discrepancies in both its environment and its body's construction [76.33]. Parameters describing the body shape (leg segment lengths, hip width, etc.) and properties of a continuous dynamical neural network controller were under genetic control. The machine started out as a passive dynamic walker [76.34] on a slope, and then throughout the evolutionary process the slope was gradually lowered to a flat surface. The machine demonstrated resistance to disturbance while retaining passive dynamic features such as a passive swing leg. Wischmann and Passemann independently took a very similar approach [76.35]. Vaughan's original machine did not have a torso, but he has also successfully applied the method to a simplified two-dimensional (2-D) machine with a torso above the hips. When pushed, this dynamically stable bipedal machine walks either forward or backwards just enough to release the pressure placed on it. It is also able to adapt to external and internal perturbations as well as variations in body size and mass [76.36]. These biped examples make use of the co-evolution of body morphology and neural controller, an idea also used in

earlier, more abstract, work on evolved bipedal locomotion by *Endo et al.* [76.37]. Although possible changes to the body morphology are quite tightly constrained, nonetheless this aspect was important. This theme is covered in more detail in the later section on Evolving Bodies, which also describes recent examples of evolved walking behaviors in the context of body-brain co-evolution.

McHale and Husbands [76.38, 39] have compared many forms of evolved neural controllers for bipedal and quadrupedal walking machines. Recurrent dynamical continuous time networks and GasNets (described

in Sect. 76.7.3) were shown to have advantages in most circumstances. The vast majority of the studies mentioned above were conducted for relatively benign environments. Notwithstanding this observation, we can conclude that the more complex dynamical neural network architectures, with their intricate dynamics, generally produce a wider range of gaits and generate smoother, more adaptive locomotion than the more standard use of systems based on finite-state machines employing parameterized rules governing the timing and coordination of individual leg movements [76.40].

76.3 Simulation and Reality

Few of the experiments in the previous section were carried out entirely on physical robots because:

1. Evolution may take a long time, especially if it is carried out on a single robot that incarnates the bodies of all the individuals of the evolving population.
2. The physical robot can be damaged because populations always contain a certain number of poorly performing individuals (for example, colliding against walls) by effect of random mutations.
3. Restoring the environment to initial conditions between trails of different individuals or populations (for example, replenishing the arena with objects) may not always be feasible without human intervention.
4. Evolution of morphologies and evolution of robots that can grow during their lifetime is almost impossible with today's technology without some level of human intervention.

For those reasons, researchers often resort to evolution in simulation and transfer the evolved controllers to the physical robot. However, it is well known that programs that work well in simulations may not function properly in the real world because of differences in sensing, actuation, and in the dynamic interactions between robot and environment [76.41]. This *reality gap* is even more evident in adaptive approaches, such as evolutionary robotics, where the control system and morphology are gradually crafted through the repeated interactions between the robot and the environment. Therefore, robots will evolve to match the specificities of the simulation, which differ from the real world. Although these issues clearly rule out any simulation based on grid worlds or pure kinematics, over the last 10 years simulation techniques have dramatically improved and resulted in software libraries that model reasonably well dynamical properties such as friction,

collision, mass, gravity, and inertia [76.42]. These software tools allow one to simulate articulated robots of variable morphology and their environment as fast as, or faster than, real time in a desktop computer.

Nonetheless, even physics-based simulations include small discrepancies that can accumulate over time and result in very different behavior from reality (for example, a robot may get stuck against a wall in simulation whereas it can get free in reality, or vice versa). Also, physics-based simulations cannot account for diversity of response profiles of the individual sensors, motors, and gears of a physical robot. Several methods can be used to cope with these problems and improve the quality of the transfer from simulation to reality.

A widely used method consists of adding independent noise to the values of the sensors provided by the model and to the end position of the robot computed by the simulator [76.43]. Some software libraries allow the introduction of noise at several levels of the simulation. This solution prevents evolution from finding solutions that rely on the specificities of the simulation model. Another method consists in sampling the actual sensor values of the real robot positioned at several angles and distances from objects of different texture. Those values are then stored in a look-up table and retrieved with the addition of noise according to the position of the robot in the environment [76.44]. This method proved to be very effective for generating controllers that transfer smoothly from simulation to reality. A drawback of this sampling method is that it does not scale up well to high-dimensional sensors (e.g., vision) or geometrically complicated objects.

Another method, also known as minimal simulations, consists of modeling only those characteristics of the robot and environment that are relevant for the emergence of desired behaviors [76.45]. These char-

acteristics, which are referred to as base-set features, should be accurately modeled in simulation. Instead, all the other characteristics, which are referred to as implementation aspects, should be randomly varied across several trials of the same individual in order to ensure that evolving individuals do not rely on implementation aspects, but rely on base-set features only. Base-set features must also be varied to some extent across trials in order to ensure some degree of robustness of the individual with respect to base-set features, but this variation should not be so large that reliably fit controllers fail to evolve at all. This method allows very fast evolution of complex robot–environment situations, as in the example of the hexapod walk described in Sect. 76.2.1. A drawback of minimal simulations is that it is not always easy to tell in advance which are the base-set features that are relevant for the desired behavior.

Yet another method consists of the coevolution of the robot (control and/or morphology) and of the simulator parameters that are most likely to differ from the real world and that may affect the quality of the transfer [76.46]. This method consists of coevolving two populations, one encoding the properties of the robot and one encoding the parameters of the simulator. Coevolution happens in several passes through a two-stage process. In stage one, a randomly generated population of robots are evolved in the default simulator and the best individual is tested on the real robot while the time series of sensory values are recorded. In stage two, the population of simulators is evolved to reduce the difference between the time series recorded on the real robot and the time series obtained by testing evolved robots within the simulator. The best evolved simulator is then used for stage one where a new randomly generated population is evolved and the best individual is tested on the real robot to generate the time series for stage

two of simulator evolution. This two-stage coevolution is repeated several times until the error between simulated and real robot behavior is the smallest possible. It has been shown that approximately 20 passes of the two-stage process are sufficient to evolve a good control system that could be transferred to an articulated robot. In that case, the real robot was used to test only 20 individuals.

A recent approach tackles the simulation to reality transfer problem by using a multi-objective formulation of ER in which two main objectives are optimized via a Pareto-based multi-objective evolutionary algorithm: (1) the fitness and (2) the transferability [76.47]. To evaluate the transferability a simulation-to-reality disparity measure was defined in terms of the difference in behavior between simulation and reality for any given controller. This measure is approximated for each member of the population and the method has successfully been demonstrated for walking behaviors [76.47].

Finally, another method consists of genetically encoding and evolving the learning rules of the control system, rather than its parameters (e.g., connection strengths). The parameters of the decoded control system are always initialized to small random values at the beginning of an individual lifetime and must self-organize using the learning rules [76.48]. This method prevents evolution from finding a set of control parameters that fit the specificities of the simulation model, and encourages emergence of control systems that remain adaptive to partially unknown environments. When such an evolved individual is transferred to the real robot, it will develop online its control parameters according to the genetically evolved learning rules and taking into account the specificities of the physical world. This method is described in more detail in Sect. 76.7.2 on evolution of learning.

76.4 Behavior as a Complex Adaptive System

Behavior is a dynamical process resulting from nonlinear interactions (occurring at a fast time rate) between the agent's control system, its body, and the environment [76.49, 50]. At any time step, the environment and the agent–environment relation influence the body and the motor reaction of the agent, which in turn influences the environment and/or the agent–environment relation (Fig. 76.7). Sequences of these interactions lead to a dynamical process where the contributions of the different aspects (i.e., the robot's control system, the robot's body, and the environment) cannot be separated. This implies that even complete knowledge of

the elements governing the interactions provides little insight into the behavior emerging from these interactions [76.51, 52].

An interesting property of evolutionary robotics is that it can enable to synthesize robots displaying a certain behavioral capacity without specifying the manner in which such capacity should be realized and/or the combination of elementary behaviors that should be produced and combined to achieve the desired overall capacity. This allows the evolving robots to discover and exploit behaviors that emerge from the interactions between the robot control system, the robot body and

the environment and/or from the interaction between previously developed behavioral capacities [76.52]. The synthesis and exploitation of emergent properties, in turn, often allows evolving robots to discover solutions that rely on relatively parsimonious control policy and/or body structures.

For an example of how evolving robots can solve an adaptive task on the basis of a simple control policy, thanks to the possibility to exploit properties emerging

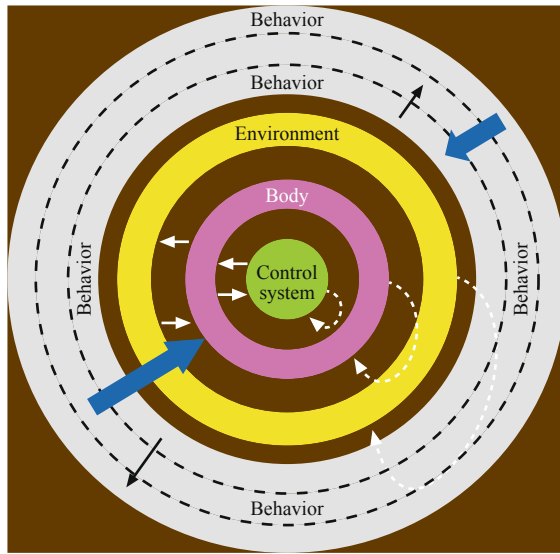


Fig. 76.7 Schematization of how: (1) behavior can emerge from several nonlinear interactions, occurring at fast time rates, between the agent's control system, its body, and the environment, and (2) behavior can display a multi-level organization in which the robot/environmental interactions and the interaction between lower-level behaviors give rise to higher level behaviors that later affect the interactions from which they originate

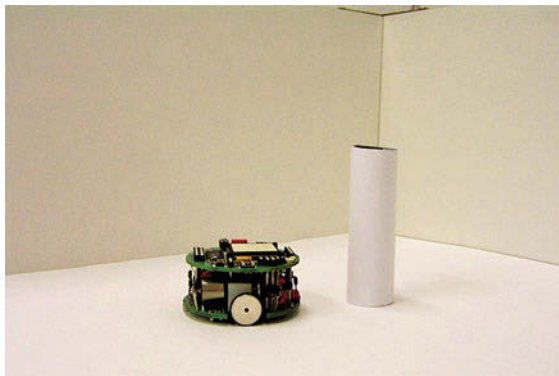


Fig. 76.8 The environment and the robot. The environment consists of an arena of 60×35 cm and contains a cylindrical objects placed at a randomly selected location

from the agent/environmental interactions, let us consider the case of a Khepera robot placed in an arena surrounded by walls (Fig. 76.8) that should evolve an ability to forage by finding and remaining close to a food object (i.e., a cylindrical object) [76.53]. The robot is provided with eight infrared sensors and two motors controlling the desired speed of the two corresponding wheels. From the point of view of an external observer, solving this problem requires robots able to:

1. Explore the environment until an obstacle is detected.
2. Discriminate whether the obstacle detected is a wall or a cylindrical object.
3. Approach or avoid the object depending on the object type.

A detailed analysis of the sensory patterns experienced by the robot indicated that the task of discriminating the two objects is far from trivial since the two classes of sensory patterns experienced by robots close to a wall and close to cylindrical objects overlap significantly. However, robots evolved for the ability to solve this task resorted to a strategy that does not require to explicitly discriminate of the two types of objects [76.53]. This solution (VIDEO 116) consists in reacting to sensory states so that the robot/environmental dynamics converge into a limit cycle near the cylindrical object, in which the robot keep moving forth and back and left and right, and not near a wall (Fig. 76.9).

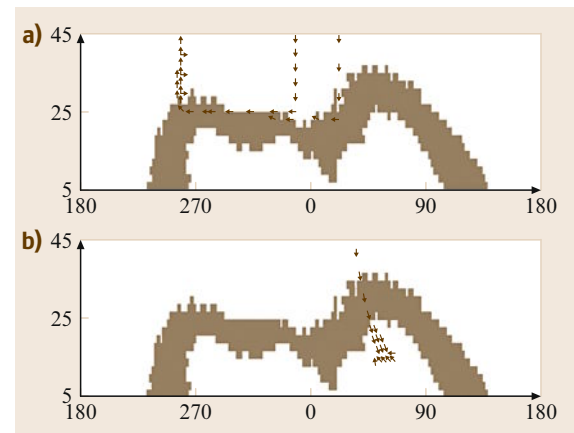


Fig.76.9a,b Angular trajectories of an evolved robot close to a wall (a) and to a cylinder (b). The picture was obtained by placing the robot at a random position in the environment, leaving it free to move for 500 cycles, and recording its relative movements with respect to the two types of objects for distances smaller than 45 mm. For sake of clarity, arrows are used to indicate the relative direction, but not the amplitude of movements

The possibility to discover and rely on these forms of emergent behavior allows evolving robots to find computationally simple solutions to apparently complex problems. Indeed, the foraging task described above can be solved by a Khepera robot provided with a simple reactive controller (i.e., a feedforward neural network with eight sensory neurons that encode the state of the corresponding infrared sensors directly connected to two motor neurons that set the desired speed of the two wheels).

76.4.1 Behavior Recombination and Re-Use

Evolving robots can recombine and re-use acquired elementary behavioral capacities to produce higher level behaviors. This has been demonstrated in a series of simulation experiments in which a population of humanoid robots provided with an articulated arm, a camera, and a touch sensor on the palm of the hand, have been evolved for the ability to execute two-words imperative sentences constituted by the combination of three action and three object words (reach, touch, move, red-object, green-object, and blue-object) encoded by six corresponding binary sensors [76.54].

During the evolutionary process the robots were evaluated for the ability to *comprehend* seven out of the nine possible sentences (that can be generated by combining the three action and the three object words) by executing the seven corresponding behaviors. The robots were then post-evaluated also on the other two sentences not experienced during the evolutionary process.

Some of the evolved robots were able to develop the required skills and to generalize their capacities to the two new sentences by executing the appropriate corresponding behaviors ( VIDEO 41). Differently from the other individuals, the robots able to generalize where characterized by a hierarchical organization in which the nine behaviors were produced by combining over time a set of elementary behaviors and in which the same elementary behaviors was re-used to produce different high-level behaviors. More specifically the robots able to generalize displayed a reach-X behavior (that consisted in moving the arm toward a red, or green, or blue object), a touch behavior (that consisted in moving the hand until the object is touched irrespectively from the color), and a move behavior (that consists in keep moving the hand also after the object has been touched irrespectively from the color) and combined these lower-level behaviors in a compositional man-

ner to produce the nine required higher-level actions. This means that, for example, the same *reach red-object* behavior was used in combination with the *touch* or the *push* behavior to produce a *touch the red-object* and a *push the red-object* behavior. For other works discussing the emergence and the role of multi-level behavioral organizations see [76.52].

76.4.2 Sensory-Motor Coordination

By acting robots inevitably modify the robot-environmental relation and/or the environment and consequently the stimuli that they will experience next. By exploiting the possibility to actively influence the perceived stimuli through actions, robots can find adaptive solutions based on parsimonious control policies. Artificial evolution constitutes an effective method for discovering such type of solutions that are often hard to imagine from the point of view of a human observer. Indeed, examples of clever use of sensory-motor coordination abounds in the evolutionary robotics literature.

Let us consider, for instance, the case of a Khepera robot endowed with infrared and wheels speed sensors, that can forage by remaining close to large cylindrical objects (food) while avoiding small cylindrical objects (dangers) [76.55]. From a passive perspective, that does not take into account the fact that the robot can self-select useful stimuli through action, the ability to discriminate between sensory stimuli experienced near small and large cylindrical objects requires a relatively complex control policy since the two classes of stimuli strongly overlap in the robot's perceptual space. On the other hand, the exploitation of sensory-motor coordination can allow the robots to simplify the discrimination problem.

Indeed, evolving robots tend to converge on a rather simple solution that consists in circling around the cylindrical objects, as soon as an object is perceived, and in using the differential speed of the left and right wheels sensed during the execution of the object-circling behavior to decide to keep circling around the object (in the case of small differential speeds) or to abandon the object (in the case of large differential speeds). Indeed, the execution of the object-circling behavior allows the robots to experience sensory stimuli on the wheel sensors that are well differentiated for small and large objects. This, in turn, allows them to solve the object discrimination problem with a rather simple but reliable control policy. For other examples see [76.53, 56, 57].

76.5 Evolving Bodies

Most evolutionary robotics experiments – and most robotics experiments in general – assume that the body plan of the robot has already been designed; an optimization method is used to improve the control policy only (The term *body plan* is here used to denote all aspects of a robot's design other than its control policy. Such design considerations include the robot's mechanical layout and material properties as well as its sensor and motor distributions.). This emphasis belies an assumption within the field of robotics, which is that control policy design is non-intuitive and thus should be automated, while choosing an appropriate robot body plan is intuitive and thus can be manually designed.

However, it has been shown that the careful design of the robot's body can have large and desirable impacts on its resulting behavior. For example, proper curvature on the underside of a biped robot's feet (along with other settings) can allow it to walk down a declined plane with no control policy at all [76.58]. Or, that modifications to an anthropomorphic robot arm and hand can facilitate the evolution of active categorical perception [76.59] (Active categorical perception occurs when a robot or animal actively interacts with objects of interest, and the sensory stimulation resulting from this physical interaction allows for categorization of those objects.). These results fit with the view of embodied behavior, as outlined in Fig. 76.7: because behavior arises from the interaction between a robot's body and its environment, alterations to the robot's body will alter the resulting behavior.

This suggests that it is useful to automatically improve not just a robot's control policy but also its body plan. Evolutionary algorithms are a uniquely well suited tool for this task because, unlike many learning methods, they do not make assumptions about the structure of the system being optimized: the length of a robot's leg – or the number of legs – can be evolved just as easily as can the strength of a synaptic connection in an artificial neural network.

76.5.1 Co-Evolving Body and Brains

The Sussex group was the first to demonstrate the evolution of robot morphology: they evolved sensor placements on a physical robot [76.15], although the other aspects of the robot's body plan remain fixed. A year later *Sims* [76.61] demonstrated an evolutionary algorithm that improved the structure and parameters of the robots' body plans and control policies. Although *Sim's creatures* were virtual and operated in a simulated environment, the robots exhibited a wide range of intuitive and non-intuitive body plans that allowed them to swim, walk or compete over a limited resource [76.62].

Funes and Pollack [76.63] demonstrated that it was possible to evolve three-dimensional forms in simulation, build them in reality, and have the physical structure act similarly to the originally-evolved simulated structure. This was followed by work from the same group in which robots evolved in simulation were manufactured as physical robots using 3-D printing technology [76.60] (Fig. 76.10). Although only the plastic frame of the robot was printed and the electronics and battery had to be manually added, this served as a demonstration that, in principle, robot design could be automated using evolutionary algorithms and robot manufacture could be automated using rapid prototyping [76.64].

Since then, a number of research groups have evolved robot body plans and control policies simultaneously for various purposes. Some researchers have adapted this approach for studying biological questions. For example *Long et al.* [76.65] have evolved the stiffness of artificial tails attached to physical swimming robots: robots with tails of differing stiffness have differing abilities to swim fast or turn well. This provides a unique experimental tool for investigating how backbones originally evolved in early vertebrates. *Clark et al.* [76.66] also evolved the material properties of part of a robot fish, but focussed in this case on evolving the stiffness and shape of its fins in simulation. This project had an engineering aim: the evolved fins were

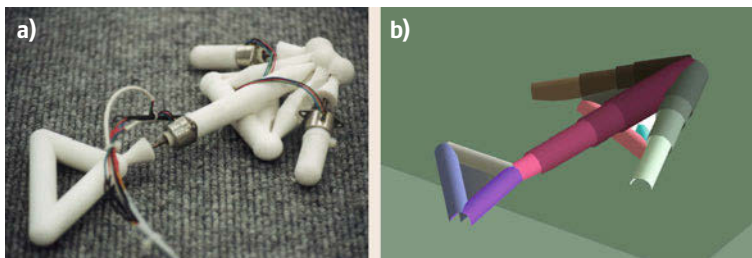


Fig.76.10a,b An example evolved robot from the GOLEM project [76.60]. (a) The virtual robot, as originally evolved in the simulated environment. (b) The physical robot comprised of a 3-D-printed plastic frame and manually-added electronics

manufactured and tested on a physical robot fish and were found to aid desirable swimming behavior.

Evolutionary algorithms can be used to explore the space of possible robot body plans, but they can also be used to explore metamorphosis, or how a robot's body plan might change over its lifetime. In recent work *Bongard* [76.67] compared two approaches to evolving walking behaviors for upright legged robots (👁️ VIDEO 771). In the first approach, upright legged robots were evolved until successful walking was discovered. In the second approach, locomotion was first evolved for legless, anguilliform robots that gradually grew legs while moving. As evolution proceeded in this second approach, later generations of robots gradually lost this infant legless body plan and instead were born with the upright, legged body plan. It was found that walking evolved for the upright legged robots more rapidly in the second approach, and that the evolved controllers were more robust. The explanation for this result is that the legless robot provides a form of scaffolding that accelerates search: it is easier for evolution to generate locomotion for the legless robot because with the anguilliform body plan the robot cannot fall over (Scaffolding is the phenomenon in which a teacher introduces some aspect into the learner's environment that helps the learner to grasp a concept and then later refine the concept when the scaffold is removed [76.68]. The canonical example of scaffolding is training wheels for bicycles.). This locomotion strategy is then refined subsequently by evolution to successfully control the upright and legged (and thus unstable) robot.

The simultaneous evolution of robot body plans and control policies offers other avenues for investigating the relationship between body, brain and environment. In [76.69] it was found that more complexly-shaped robots were produced when evolved to walk over rough terrain than when evolved to walk over flat terrain (👁️ VIDEO 772). This was due to the fact that robots evolved in rough terrain evolved appendages and hooks to gain purchase between outcroppings and then pull or push themselves forward.

Most recently *Hiller* and *Lipson* [76.70] have demonstrated the evolution of soft robots: this requires evolving not just the control policy of the robot and its physical shape, but also the material properties of each voxel comprising the machine. This allows for complex three-dimensional patterning of soft and rigid material throughout the robot, which can be exploited by evolution to produce locomotion [76.71]. Soft robots are an ideal vehicle for demonstrating the power of evolutionary algorithms: the design and control of such machines is highly nonintuitive, making manual design extremely difficult.

76.5.2 Self-Modeling

The evolution of robot body plans can be useful not just for robot design but also for increasing the adaptivity of a physical robot once it has been designed and deployed. For example in [76.72] it was shown that a physical robot could be equipped with an on-board simulator that the robot could use to continuously evolve models of itself. These self-models reflect the mechanical construction of the robot. This method was found useful for robots that might sustain unanticipated damage such as the mechanical separation of a leg: the robot diagnoses the damage; it then evolves a simulated damaged robot that accurately reflects the physical damage; it evolves a compensatory control policy internally using the simulated, damaged robot; and finally the physical robot uses the internally evolved compensatory control policy to continue moving despite its injury. Figure 76.11 outlines this method.

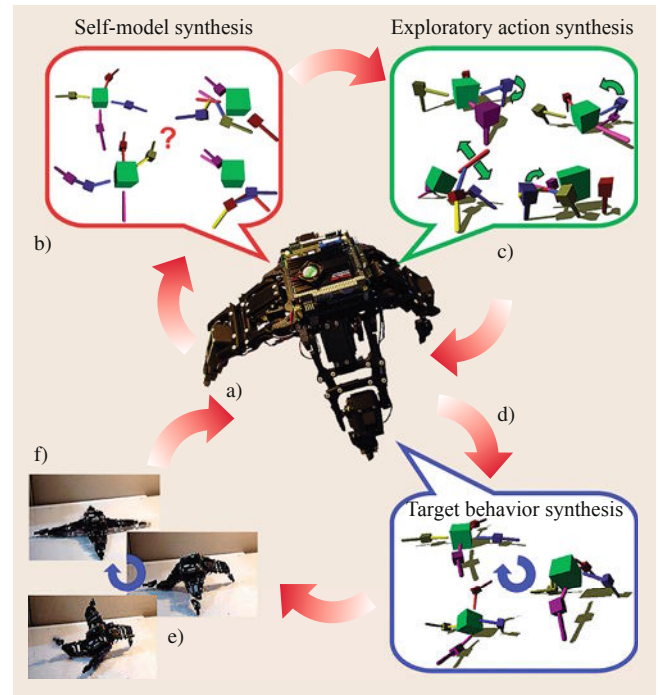


Fig.76.11a–f The machine begins by performing a random action and collects the resulting sensor-motor data (a). An evolutionary algorithm evolves a population of simulated robots that, when they move, produce similar sensor-motor data as the physical machine (b). Another algorithm searches for a new action for the physical robot to perform (c). The physical robot performs the new action, and re-evolves self-models to explain the result of the first action and the new action ((a)). After several cycles of this self-modeling, the best self-model is used to evolve new behaviors (d). Finally, the physical robot executes these newly-evolved behaviors (e,f)

A method for generalizing this to robot swarms was demonstrated in [76.73]. Each robot in the swarm maintained its own self-modeling engine, but would periodically export its best self-model and control policy to others in the swarm. The result of this was that if one robot was damaged and recovered, a second robot that suffered similar damage recovered more rapidly.

Finally, instead of modeling the self, a robot could create a model of another robot in its vicinity. Even bet-

ter, the robot could evolve a model of the other robot's intentions and use this information to aid or thwart the other robot's actions, as demonstrated in [76.74]. Although the robots did not model each other's body plans, this ability to model others in general is known as Theory of Mind. One could imagine how increasing levels of recursion of such embedded mind reading could provide continued evolutionary pressure toward increasingly intelligent machines.

76.6 Seeing the Light

Pioneering experiments on evolving visually guided behaviors were performed at Sussex University [76.75] on a specially designed gantry robot (Fig. 76.12, see also  VIDEO 371). Discrete-time dynamical recurrent neural networks and visual sampling morphologies were concurrently evolved: the brain was developed in tandem with the visual sensor [76.13, 76.77]. The robot was designed to allow real-world evolution by having *off-board* power and processing so that the robot could be run for long periods while being monitored by automatic fitness evaluation functions. A charge-coupled device (CCD) camera points down towards a mirror angled at 45° as shown in Fig. 76.12. The mirror can rotate around an axis perpendicular to the camera's image plane. The camera is suspended from the gantry, allowing motion in the X , Y , and Z dimensions. This effectively provides an equivalent to a wheeled robot with a forward-facing camera when only the X and Y dimensions of translation are used. The additional dimension allows flying behaviors to be studied.

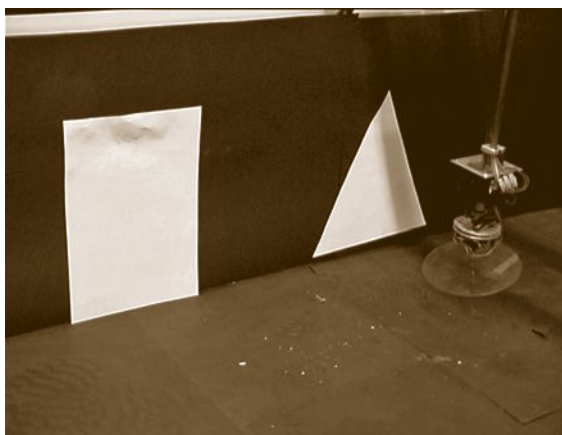


Fig. 76.12 The gantry robot used in the visual discrimination task. The camera inside the top box points down at the inclined mirror, which can be turned by the stepper motor beneath. The lower plastic disk is suspended from a joystick to detect collisions with obstacles

The apparatus was initially used in a manner similar to the real-world experiments on navigation in the looping maze with the miniature mobile robot described in Sect. 76.2. A number of visually guided navigation behaviors were successfully achieved, including navigating around obstacles, tracking moving targets, and discriminating between different objects [76.76]. The evolutionary process was incremental. The ability to distinguish between two different targets was evolved on top of the single target-finding behavior. The chromosome was of dynamic length so the neurocontroller was structurally further developed by evolution to achieve the new task (neurons and connections added). In the experiment illustrated in Figs. 76.12 and 76.13,

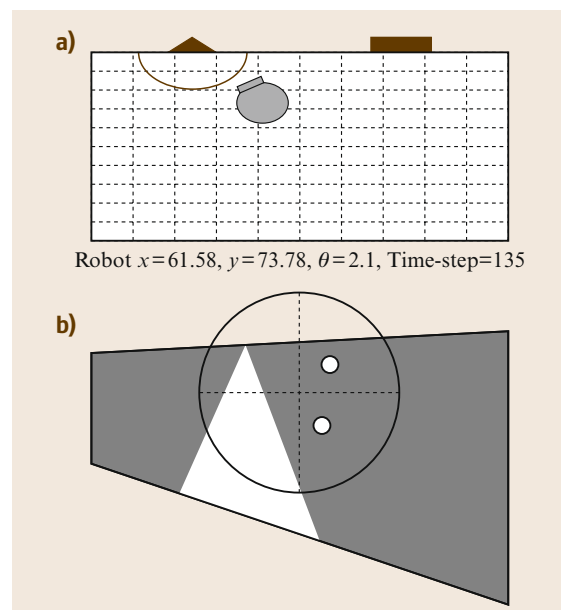


Fig. 76.13a,b The shape discrimination task. (a) The position of the robot in the arena, showing the target area in front of the triangle. (b) The robot camera's field of view showing the visual patches selected by evolution for sensory input

starting from a random position and orientation, the robot had to move to the triangle rather than the rectangle. This had to be achieved irrespective of the relative positions of the shapes and under very noisy lighting conditions. Recurrent neural network controllers were evolved in conjunction with visual sampling morphologies. Only genetically specified patches from the camera image were used (by being connected to input neurons according to the genetic specification). The rest of the image was thrown away. This resulted in extremely minimal systems using only two or three pixels of visual information, yet still able to perform the task reliably under highly variable lighting conditions [76.13, 76].

This was another example of staged, or incremental, evolution to obtain control systems capable of solving problems that are either too complex or may profit from an evolutionary methodology that discovers, preserves, and builds upon subcomponents of the solution. For an evolutionary method that incorporate strategies to explicitly address this issue, interested readers may refer to [76.78]. However, staged evolution remains a poorly explored area of evolutionary robotics that deserves further study and a more principled approach [76.79] in order to achieve increasingly complex robotic systems.

76.6.1 Coevolution of Active Vision and Feature Selection

Machine vision today can hardly compete with biological vision despite the enormous power of computers. One of the most remarkable – and often neglected – differences between machine vision and biological vision is that computers are often asked to process an entire image in one shot and produce an immediate answer whereas animals take time to explore the image over time, searching for features and dynamically integrating information over time.

Active vision is the sequential and interactive process of selecting and analyzing parts of a visual scene [76.80–82]. *Feature selection* instead is the development of sensitivity to relevant features in the visual scene to which the system selectively responds, e.g., [76.83]. Each of these processes has been investigated and adopted in machine vision. However, the combination of active vision and feature selection is still largely unexplored. An intriguing hypothesis is that coevolution of active vision and feature selection could greatly simplify the computational complexity of vision-based behavior by facilitating each other's task.

This hypothesis was investigated in a series of experiments [76.84] on coevolution of active vision and feature selection for behavioral systems equipped with

a primitive moving retina and a deliberately simple neural architecture (Fig. 76.14). The neural architecture was composed of an artificial retina and two sets of output units. One set of output units determined the movement and zooming factor of the retina, and the other set of units determined the behavior of the system, such as the response of a pattern-recognition system, the control parameters of a robot, or the actions of a car driver. The neural network was embedded in a behavioral system and its input/output values were updated every 300 ms while its fitness was computed. Therefore, the synaptic weights of this network were responsible for both the visual features on which the system based its behavior and for the motor actions necessary to search for those features.

In a first set of experiments, the neural network was embedded in a simulated pan-tilt camera and asked to discriminate between triangles and squares of different size that could appear at any location of a screen (Fig. 76.15a), a perceptual task similar to that explored with the gantry robot described in Sect. 76.5. The visual system was free to explore the image for 60 s while continuously reporting whether the current screen showed a triangle or a square. The fitness was proportional to

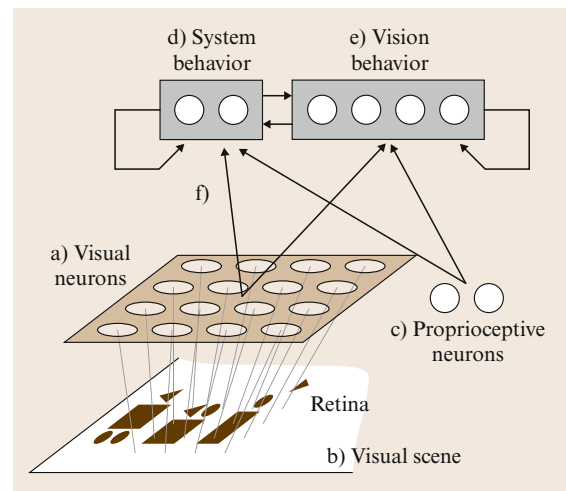


Fig. 76.14a–f The neural architecture of the active vision system is composed of: (a) a grid of visual neurons with nonoverlapping receptive fields whose activation is given by (b) the grey level of the corresponding pixels in the image; (c) a set of proprioceptive neurons that provide information about the movement of the vision system; (d) a set of output neurons that determine the behavior of the system (pattern recognition, car driving, robot navigation); (e) a set of output neurons that determine the behavior of the vision system; and (f) a set of evolvable synaptic connections. The number of neurons in each subsystem can vary according to the experimental settings

the amount of correct responses accumulated over the 60 s for several screenshots containing various instances of the two shapes. Evolved systems were capable of correctly identifying the type of shape with 100% accuracy after a few seconds despite the fact that this recognition problem is not linearly separable and that the neural network does not have hidden units, which in theory are necessary to solve nonlinearly separable tasks. Indeed, the same neural network presented with the same set of images and trained with supervised learning, but without the possibility to actively explore the scene, was not capable of solving the task. The evolved active vision system developed sensitivity to vertical edges, oriented edges and corners, and used its movement to search for these features in order to tell whether the shape was a triangle or a square. These features, which are also found in the early visual system of almost all animals, are invariant to size and location.

In a second set of experiments, the neural network was embedded in a simulated car and was asked to drive over several mountain circuits (Fig. 76.15b). The simulator was a modified version of a car race video game. The neural network could move the retina across the scene seen through the windscreen at the driver's seat and control the steering, acceleration, and braking of the car. The fitness was inversely proportional to the time taken to complete the circuits without exiting the road. Evolved networks completed all circuits with time laps competitive to those of well-trained students controlling the car with a joystick. The evolved network started by searching for the edge of the road and tracked its relative position with respect to the edge of the windscreen in order to control steering and acceleration. This behavior was supported by the development of sensitivity to oriented edges.

In a third set of experiments, the neural network was embedded in a real mobile robot with a pan-tilt camera

that was asked to navigate in a square arena with low walls located in an office (Fig. 76.16). The fitness was proportional to the amount of straight motion measured over two minutes. Robots that hit the walls because they watched people or other irrelevant features of the office had lower fitness than robots that could perform long straight paths and avoid walls of the arena. Evolved robots tended to fixate the edge between the floor and the walls of the arena, and turned away from the wall when the size of its retinal projection became larger than a threshold (👁️ VIDEO 36). This combination of sensitivity to oriented edges and looming is also found in the visual circuits of several insects and birds.

In a further set of experiments [76.85], the visual pathway of the neural network was augmented by an intermediate set of neurons whose synaptic weights could be modified by Hebbian learning [76.86] while the robot moved in the environment. All the other synaptic weights were genetically encoded and evolved. The results showed that lifelong development of the receptive fields improved the performance of evolved robots and allowed robust transfer of evolved neural controllers from simulated to real robots, because the receptive fields developed sensitivity to features encountered in the environment where they happen to be born (see also the section above on simulation and reality). Furthermore, the results showed that the development of visual receptive fields was significantly and consistently affected by active vision as compared to the development of receptive fields passively exposed to the same set of sample images. In other words, robots evolved with active vision developed sensitivity to a smaller subset of features in the environment and actively tracked those features to maintain a stable behavior.

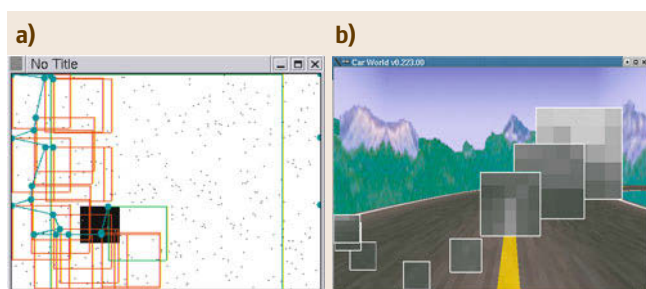


Fig. 76.15 (a) An evolved individual explores the screen searching for the shape and recognizes it by the presence of a vertical edge. (b) Search for the edge of the road at the beginning of a drive over a mountain road



Fig. 76.16 A mobile robot with a pan-tilt camera is asked to move within the walled arena in the office environment

76.7 Computational Neuroethology

Evolutionary robotics is also used to investigate open questions in neuroscience and cognitive science [76.87–90] because it offers the vantage point of a behavioral system that interacts with its environment [76.91]. Although the results should be carefully considered when drawing analogies with biological organisms, evolutionary robotics can generate and test hypotheses that could be further investigated with mainstream neuroscience methods.

For example, the active vision system with Hebbian plasticity described in the previous section was used to answer a question raised by *Held* and *Hein* [76.92] in the 1960s. The authors devised the apparatus shown in Fig. 76.17 where the free movements of a kitten (*active kitten*) were transmitted to a second kitten that was carried in a gondola (*passive kitten*). The second kitten could move its head, but its feet did not touch the ground. Consequently, the two kittens received almost identical visual stimulation, but only one of them received that stimulation as a result of body self-movement. After a few days in that environment, only the active kitten displayed normal behavior in several visually guided tasks. The authors suggested the hypothesis that proprioceptive motor information resulting from generation of actions was necessary for the development of normal, visually guided behavior.

The kitten experiments were replicated by cloning an evolved robot controller and randomly initializing the synaptic values of the adaptive visual pathways in both clones. One cloned robot was then left free to move in a square environment while the other cloned robot was forced to move along imposed trajectories, but was free to control its camera position, just like the passive kitten [76.94]. The results indicated that the visual receptive fields and behaviors of passive robots differ significantly from those of active robots. Furthermore, passive robots that were later left free to move were no longer capable of properly avoiding walls. A thorough analysis of neural activation correlated with behavior of the robot and even transplantation of neurons across active and passive robots revealed that the poor performance was due to the fact that passive robots could not completely select the visual features they were exposed to. Consequently, passive robots developed sensitivity to features that were not functional to their normal behavior and interfered with other dominant features in the visual field. Whether this explanation also holds for living animals remains to be further investigated, but at least these experiments indicated that motor feedback is not necessary to explain the pattern of pathological behavior observed in animals and robots.

76.7.1 Emergence of Place Cells

Let us now consider the case of an animal exploring an environment and periodically returning to its nest to feed. It has been speculated that this type of situation requires the formation of spatial representations of the environment that allow the animal to find its way home [76.95]. Different neural models with various degrees of complexity and biological detail that could provide such functionality have been proposed [76.96, 97].

Would a robot evolved under similar survival conditions develop a spatial representation of the environment and, if so, what type of representation would that be? These questions were explored using the same Khepera robot and evolutionary methodology described in Sect. 76.2 for reactive navigation in the looping maze. The environment was a square arena with a small patch on the floor in a corner where the robot could instantaneously recharge its (simulated) battery (Fig. 76.18). The environment was located in a dark room with a small light tower over the *recharging station*.

The sensory system of the robot was composed of eight distance sensors, two ambient-light sensors (one

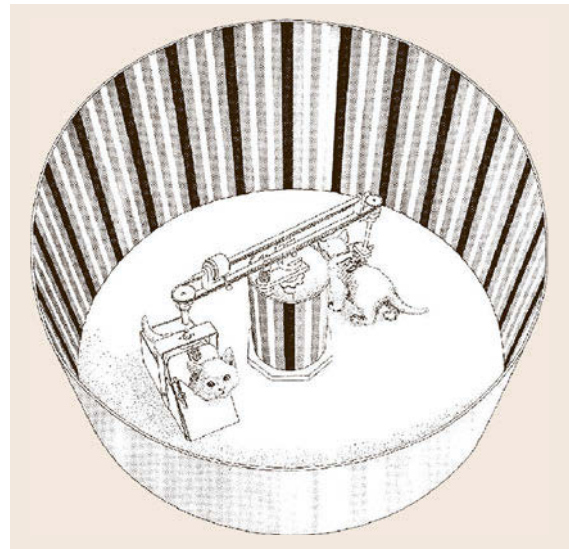


Fig. 76.17 The original apparatus in [76.92], where the gross movements of a kitten moving almost freely were transmitted to a second kitten that was carried in a gondola. Both kittens were allowed to move their head. They received essentially the same visual stimulation because of the unvarying pattern on the walls and the center post of the apparatus (after [76.93], with permission)

on each side), one floor-color sensor, and a sensor for battery charge level. The battery lasted only 20 s and had a linear discharge. The evolutionary neural network included five fully connected internal neurons between sensory and motor neurons. The same fitness function described in Sect. 76.2 for navigation in the looping maze was used, except for the middle term which had been used to encourage straight navigation in the looping maze. The fitness value was computed every 300 ms and accumulated over the life span of the individual. Therefore, individuals who discovered where the charger was could live longer and accumulate more fitness by exploring the environment (individuals were killed if they survived longer than 60 s to limit the experimentation time).

The same physical robot evolved for 10 days and nights as both the fitness and life span of individuals continued to increase (Fig. 76.19). After approximately 200 generations, the robot was capable of navigating around the environment, covering long trajectories while avoiding both walls and the recharging area (VIDEO 118). When the battery was almost discharged it initiated a straight navigation towards the recharging area and exited immediately after battery recharge to resume navigation. Best evolved individuals always entered the recharging area one or two seconds before full discharge of the battery. That implies that robots must somehow calibrate the timing and trajectory of their homing behavior depending on where they happened to be in the environment.

In order to understand how that behavior could possibly be generated, a set of neuroethological measures

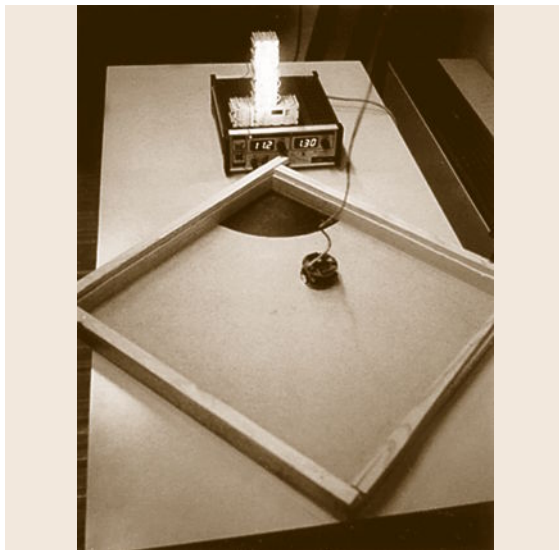


Fig. 76.18 Bird's eye view of the arena with the light tower over the recharging station and the Khepera robot

were performed using a laser positioning device that provided exact position and orientation of the robot every 300 ms. By correlating the robot position and behavior with the activation of the internal neurons in real time while the evolved individual freely moved in the environment, it was possible to see that some neurons specialized for reactive behaviors, such as obstacle avoidance, forward motion, and battery monitoring. Other neurons instead displayed more complex activation patterns. One of them revealed a pattern of activation levels that depended on whether the robot was oriented facing the light tower or facing the opposite direction (Fig. 76.20). In the former case, the activation pattern reflected zones of the environment and paths typically followed by the robot during exploration and homing. For example, the robot trajectory towards the recharging area never crossed the two *gate walls* visible in the activation maps around the recharging station. When the robot faced the opposite direction, the same neuron displayed a gradient field orthogonally aligned with the recharging area. This gradient provides an indication of the distance from the recharging area. Interestingly, this pattern of activity is not significantly affected by the charge level of the battery.

The functioning of this neuron reminds of the classic findings on the hippocampus of the rat brain where some neurons (also known as *place cells*) selectively fire when the rat is in specific areas of the environment [76.98]. Also, the orientation-specific pattern of neural activation measured on the evolved robot is rem-

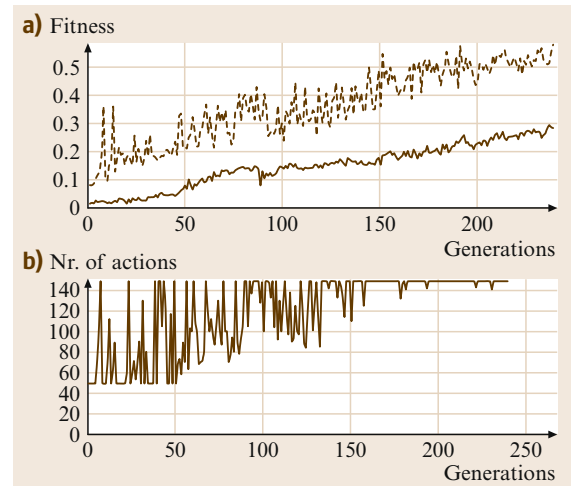


Fig. 76.19 (a) Average population fitness (*continuous line*) and fitness of the best individual (*dotted line*). (b) Life span of the best individuals measured as number of sensorimotor cycles, or actions. Individuals start with a full battery which lasts 50 actions (20 s), if not recharged. The maximum life span is 150 actions

inherent of the so-called *head-direction neurons* in the rat hippocampus, which are positioned nearby place cells, whose firing patterns depend on the rat heading direction with respect to an environmental landmark [76.99]. Although the analogy between brains of evolved robots and of biological organisms should not be taken too literally, these results indicate that the two organisms converge towards a functionally similar neural strategy, which may be more efficient to address this type of situation than a strategy that does not rely on representations (but only on reactive strategies such as random motion, light following, or dead reckoning).

76.7.2 Spiking Neurons

The great majority of biological neurons communicate using self-propagating electrical pulses called *spikes*, but from an information-theoretic perspective it is not yet clear how information is encoded in the spike train. Connectionist models [76.100], by far the most widespread, assume that what matters is the *firing rate* of a neuron, that is, the average quantity of spikes emitted by the neuron within a relatively long time window (for example, over 100 ms). Alternatively, what matters is the average number of spikes of a small population of neurons at a give point. In these models the real-valued output of an artificial neuron represents the firing rate, possibly normalized relatively to the maximum attainable value. Pulsed models [76.101], instead, are based on the assumption that the *firing time*, that is, the precise time of emission of a single spike, may convey important information [76.102]. Spiking neuron models have slightly more complicated dynamics of synaptic and membrane integration. Depending on one's theory of what really matters, connectionist or spiking models are used.

However, designing circuits of spiking neurons that display a desired functionality is still a challenging task. The most successful results in the field of robotics obtained so far focused on the first stages of sensory processing and on relatively simple motor control [76.103, 104]. Despite these implementations, there are not yet methods for developing complex spiking circuits that could display minimally cognitive functions or learn behavioral abilities through autonomous interaction with a physical environment.

Artificial evolution represents a promising methodology to generate networks of spiking circuits with desired functionalities expressed as behavioral criteria (fitness function). Evolved networks could then be examined to detect what communication modality is used and how that correlates with observed behavior of the robot.

Floreano and Mattiussi [76.105] evolved a fully connected network of spiking neurons for driving a vision-based robot in an arena painted with black stripes of variable size against a white background (Fig. 76.21). The Khepera robot used in these experiments was equipped with a vision turret composed of one linear array of grayscale photoreceptors spanning a visual field of 36° . The output values of a bank

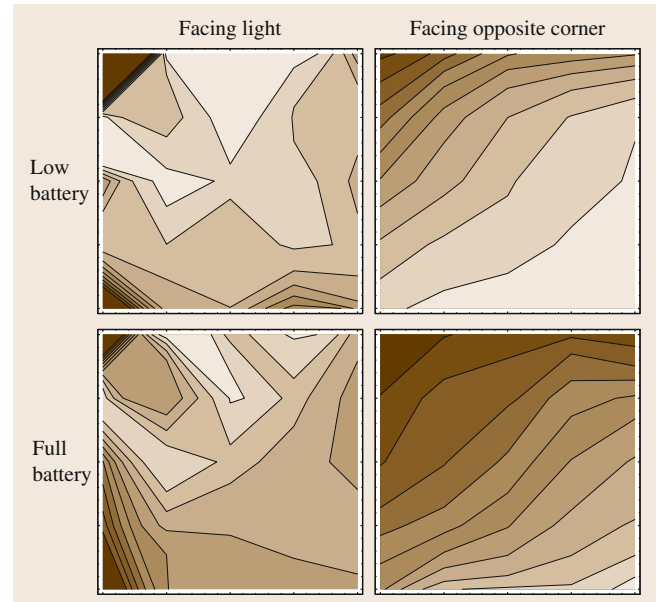


Fig. 76.20 Activation levels (brightness proportional to activation) of an internal neuron plotted over the environment while the robot was positioned at various locations in each of the four conditions (facing recharging area or not, discharged battery or not). The recharging area is located at the *top left corner* of each map

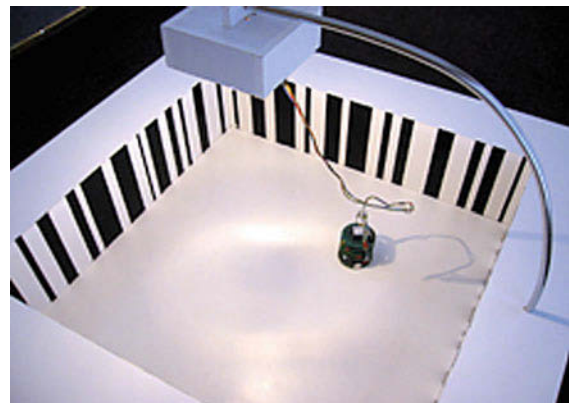


Fig. 76.21 A network of spiking neurons is evolved to drive the vision-based robot in the arena. The light below the rotating contacts allows continuous evolution also overnight

of local contrast detection filters were converted in spikes (the stronger the contrast, the larger the number of spikes per second) sent to ten fully connected spiking neurons implemented according to the spike response model [76.106]. The spike series of a subset of these neurons was translated into motor commands (more spikes per second corresponded to faster rotation of the wheel). The fitness function was the amount of forward translation of the robot measured over 2 min. Consequently robots that turned in place or hit the walls had comparatively lower fitness than robots that could move straight and turn only to avoid walls. The genome of these robots was a bit string that encoded only the sign of the neurons and the presence of synaptic connections. Existing connections were set to 1 and could not change during the lifetime of the robot.

Evolution reliably discovered very robust spiking controllers in approximately 20 generations, approximately 30 h of evolution on the real robot (VIDEO 37). Evolved robots could avoid not only the walls, but any object positioned in front of them. Detailed analysis of the best evolved controllers revealed that neurons did not exploit time differences between spikes, which one would have expected if optic flow was used to detect distance from walls. Instead, they simply used the number of incoming spikes (firing rate) as an indication of when to turn. When the robot perceived a lot of contrast it would go straight, but when the contrast decreased below a certain threshold (indicating that it approached an object), it started to turn away. This extremely efficient and simple result seems to be in contrast with theories of optic flow detection in insects and may be worth considering as an alternative hypothesis for vision-based behavior.

Spiking neural networks turned out to be more evolvable than connectionist models (at least for this task). One possible explanation is that spiking neurons have subthreshold dynamics that, to some extent, can be affected by mutations without immediately affecting the output of the network.

The robust results and compact genetic encoding encouraged the authors to use an even simpler model of spiking neuron so that the entire neural network could be mapped in less than 50 bytes of memory. The evolutionary algorithm was also reduced to a few lines of code and the entire system was implemented within a programmable intelligent computer (PIC) microcontroller without the need for any external computer for data storage. The system was used for a sugar-cube robot (Fig. 76.22) that autonomously and reliably developed the ability to navigate around a maze in less than an hour [76.107]. Interestingly, evolved spiking controllers developed a pattern of connections where

spiking neurons received connections from a small patch of neighboring sensors, but not from other sensors, and were connected only to neighboring spiking neurons. This pattern of connectivity is also observed in biological systems and encourages specialization of neurons to sensory features.

76.7.3 GasNets

This section describes another style of artificial neural network strongly inspired by those parts of contemporary neuroscience that emphasize the complex electrochemical nature of real nervous systems. In particular, they make use of an analogue of *volume signaling*, whereby neurotransmitters freely diffuse into a relatively large volume around a nerve cell, potentially affecting many other neurons [76.108, 109]. This exotic form of neural signaling does not sit easily with classical pictures of brain mechanisms and is forcing a radical rethink of existing theory [76.110–113]. The class of artificial neural networks developed to explore artificial volume signaling are known as GasNets [76.114]. These are essentially standard neural networks augmented by a chemical signaling system comprising a diffusing *virtual* gas which can modulate the response of other neurons. A number of GasNet variants, inspired by different aspects of real nervous systems, have been explored in an evolutionary robotics context as artificial nervous systems for mobile autonomous robots. They have been shown to be significantly more evolvable, in terms of speed to a good solution, than other forms of neural networks for a variety of robot tasks and behaviors [76.38, 114–116]. They are being investigated as potentially useful engineering tools and as a way of gaining helpful insights into biological systems [76.112, 117–119].

By analogy with biological neuronal networks, GasNets incorporate two distinct signaling mechanisms, one *electrical* and one *chemical*. The underlying *electrical* network is a discrete-time-step recurrent neural network with a variable number of nodes. These nodes

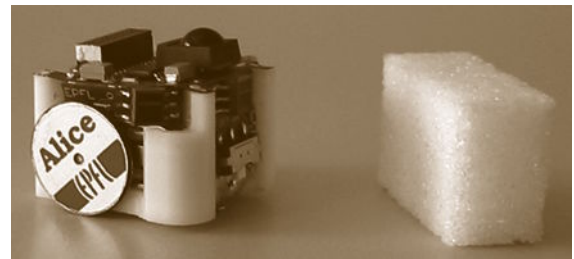


Fig. 76.22 The Alice sugar-cube robot equipped with the evolutionary spiking neural network implemented within its PIC microcontroller

are connected by either excitatory or inhibitory links (Fig. 76.23).

In addition to this underlying network in which positive and negative *signals* flow between units, an abstract process loosely analogous to the diffusion of gaseous modulators is at play. Some units can emit virtual *gases* which diffuse and are capable of modulating the behavior of other units by changing the profile of their output functions. The networks occupy a 2-D space; the diffusion processes mean that the relative positioning of nodes is crucial to the functioning of the network. Spatially, the gas concentration varies as an inverse exponential of the distance from the emitting node with a spread governed by a parameter r with the concentration set to zero for all distances greater than r . The total concentration of gas at a node is determined by summing the contributions from all other emitting nodes.

For mathematical convenience, in the original GasNet there are two *gases*, one whose modulatory effect is to increase the transfer function gain parameter and one whose effect is to decrease it. Thus the gas does not alter the electrical activity in the network directly but rather acts by continuously changing the mapping between input and output for individual nodes, either directly or by stimulating the production of further virtual gas. The general form of the diffusion is based on the properties of a (real) single-source neuron as modeled in detail by Philippides et al. [76.112, 117]. The modulation chosen is motivated by what is known of NO modulatory effects at synapses [76.120]. For full details see [76.114].

Various extensions of the basic GasNet have been produced. Two in particular are strongly inspired by contemporary neuroscience. The *plexus model* is directly inspired by a type of signaling seen in the mammalian cerebral cortex in which the NO signal is generated by the combined action of many fine NO-producing fibers, giving a targeted *cloud* which is distant from the neurons from which the fiber plexus emanates [76.118]. In the plexus GasNet, which models this form of signaling at an abstract level, the spatial distribution of gas concentration has been modified to be uniform over the area of affect. The center of this gas diffusion cloud is under genetic control and can be distant from the controlling node (which, by analogy, is the source of the *plexus*) [76.116]. All other details of the models are identical to the original GasNet model, as described earlier. The *receptor GasNet* incorporates an aspect of biological neuronal networks that has no analog in the vast majority of artificial neural networks (ANNs): the role of receptor molecules. Although neuroscience is a long way from a full understanding of receptor mechanisms, a number of powerful systems level ideas can be abstracted.

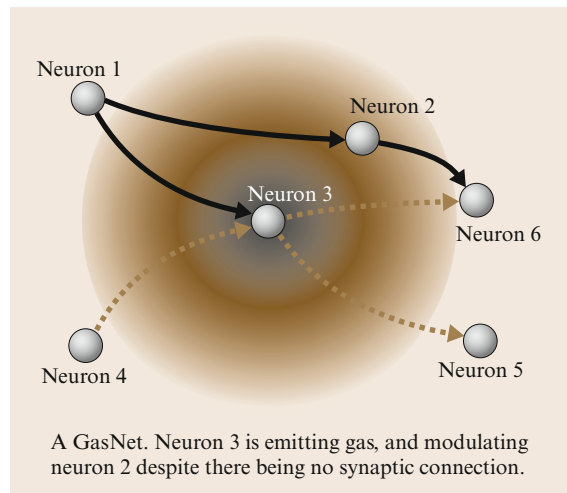


Fig. 76.23 A basic GasNet showing positive (solid) and negative (dashed) electrical connections and a diffusing virtual gas creating a *chemical gradient*

Details of the receptor variant are similar to the basic GasNet except there is now *only one* virtual gas and each node in the network can have one of three discrete quantities (zero, medium, maximum) of a number of possible receptors. The modulation the diffusing neurotransmitter affects at a neuron depends on which receptors are present. The strength of a modulation at a node is proportional to the product of the gas concentration at the node and the relevant receptor quantity. In the original GasNet, any node that was in the path of a diffusing transmitter would be modulated in a fixed way. The receptor model allows site-specific modulations, including no modulation (no receptors) and multiple modulations at a single site ([76.116] for further details).

Although most of the GasNet variants described in this section have been successfully used in a number of robotic tasks, their evolvability and other properties were thoroughly compared on a version of the (gantry) robot visual discrimination task described in Sect. 76.5, [VIDEO 375](#). All aspects of the networks were under genetic control: the number of nodes, the connectivity and, in the case of the GasNets, all parameters governing volume signaling (including the position of the nodes and whether or not they were *virtual gas* emitters). The visual sampling morphology was also under evolutionary control. The original basic GasNet was found to be significantly more evolvable than a variety of other styles of connectionist neural networks as well as a GasNet with the volume signaling disabled. Successful GasNet controllers for this task tended to be rather minimal, in terms of numbers of nodes and connections, while possessing complex dynamics [76.114].

Later experiments comparing the basic GasNet with the plexus and receptor variants showed the latter two to be considerably more evolvable than the former, with the receptor GasNet being particularly successful [76.116]. These GasNet experiments demonstrated that the intricate network dynamics made possible by the artificial volume signaling mechanisms can be readily harnessed to generate adaptive behaviors in autonomous agents. They also throw up such questions as why GasNets are more evolvable than many other forms of ANN and why there is a difference in evolvability between GasNet variants. In order to gain insight into what factors are most important in GasNet evolvability, several other varieties were studied, including non-spatial GasNets where the diffusion process is replaced by explicit gas connections with complex dynamics and version with other forms of modulation and diffusion [76.119]. Detailed comparative studies of these variants with each other, and with other forms of ANN, were performed using the visual discrimination task described above [76.116, 119].

The comparative studies revealed that the rich dynamics and additional timescales introduced by the gas played an important part in enhanced evolvability, but were not the whole story [76.116, 119]. The particular form of modulation was also important – multiplicative or exponential modulation (in the form of changes to the transfer function) were found to be effective, but additive modulations were not. The former kind of modulations may well confer evolutionary advantages by allowing nodes to be sensitive to different ranges of input (internal and sensory) in different contexts. The spatial embedding of the networks also appears to play a role in producing the most effective coupling between the two distinct signalling processes (*electrical* and *chemical*). By exploiting a loose, flexible coupling between the two processes, it is possible to significantly reduce destructive interference between them, allowing one to be *tuned* against the other while searching for good solutions [76.115, 116, 121]. Similar forces may be at play in spiking neural networks, where sub-threshold and spiking dynamics interact with each other, which although not yet compared to GasNets, were shown to be more evolvable than connectionist networks. Measurements of the degree of coupling in the GasNets variants versus speed of evolution supported this view [76.116]; the receptor GasNet, for

which the evolutionary search process has the most direct control over the degree of coupling between the signaling processes, and which has a bias towards a loose coupling, was by far the most evolvable [76.116].

Analysis of GasNet solutions often reveals high levels of degeneracy, with functionally equivalent sub-networks occurring in many different forms, some involving gas and some not [76.121]. Their genotype to phenotype mapping (where the phenotype is robot behavior) is also highly degenerate with many different ways of achieving the same outcome (e.g., moving node positions, changing gas diffusion parameters or adding new connections can all have the same effect). This is especially true when variable length genotypes are used to efficiently sculpt solutions in a search space of variable dimensions. The levels of degeneracy are generally significantly higher than when using connectionist networks. These properties partly explain the robustness and adaptability of GasNets in noisy environments and are another important factor in their evolvability (there are many paths to the same phenotypical outcome with reduced probabilities of lethal mutations) [76.119, 122]. In the most successful varieties of GasNet, multi-scale dynamics, modulation and spatial embedding act in concert to produce highly evolvable degenerate networks.

These and ongoing investigations indicate that explicitly dealing with the electrochemical nature of nervous systems is likely to be an increasingly fruitful area of research, both for evolutionary robotics and for neuroscience, that will likely force us to broaden our notions of what behavior-generating mechanisms might look like.

Because of its ability to explore whole classes of underspecified models, ER is being increasingly used to develop or explore neural models aimed at answering specific questions in neuroscience [76.88–90] or to probe new theories about possible neural mechanisms [76.90]. One intriguing recent hypothesis is that one of the forms of plasticity on which the brain relies is itself a form of evolution via natural selection acting within neural tissue [76.123, 124]. The units of selection in this case are activity and connection patterns which are copied between groups of neurons. Irrespective of whether or not it occurs in nature (and it might), this kind of mechanism could be employed in a whole new kind of evolutionary robotics.

76.8 Evolution and Learning

Evolution and learning (or phylogenetic and ontogenetic adaptation) are two forms of biological adaptation that differ in space and time. Evolution is a process

of selective reproduction and substitution based on the existence of a population of individuals displaying variability at the genetic level. Learning, instead,

is a set of modifications taking place within each single individual during its own life time. Evolution and learning operate on different time scales. Evolution is a form of adaptation capable of capturing relatively slow environmental changes that might encompass several generations (e.g., the perceptual characteristics of food sources for a given species). Learning, instead, allows an individual to adapt to environmental modifications that are unpredictable at the generational level. Learning might include a variety of mechanisms that produce adaptive changes in an individual during its lifetime, such as physical development, neural maturation, variation of the connectivity between neurons, and synaptic plasticity. Finally, whereas evolution operates on the genotype, learning affects only the phenotype, and phenotypic modifications cannot directly modify the genotype.

Researchers have combined evolutionary techniques and learning techniques (supervised or unsupervised learning algorithm such as reinforcement learning or Hebbian learning; for a review see [76.125]). These studies have been conducted with two different purposes:

1. Identifying the potential advantage of combining these two methods from the point of view of developing robust and effective robots.
2. Understanding the role of the interaction between learning and evolution in nature.

Within an evolutionary perspective, learning has several different adaptive functions. First, it might allow individuals to adapt to changes that occur too quickly to be tracked by evolution [76.126]. Secondly, learning might allow robots to use information extracted during their interaction with environment to develop adaptive characters ontogenetically without necessarily discovering these characters through genetic variations and without encoding these characters in their genome. To understand the importance of this aspect, we should consider that evolutionary adaptation is based on an explicit but concise indication of how well an individual robot coped with its environment – the fitness value of a robot. Ontogenetic adaptation, on the contrary, is based on extremely rich information – the state of the sensors while the robot interacts with its environment. This huge amount of information encodes very indirectly how well an individual is doing in different phases of its lifetime or how it should modify its behavior to increase its fitness. However, evolving robots that have acquired a predisposition to exploit this information to produce adaptive changes during their lifetime might be able to develop adaptive characteristics on the fly, thus leading to the possibility to

produce *complex* phenotypes on the basis of parsimonious genotypes. Finally, learning can help and guide evolution. Although physical changes of the phenotype, such as strengthening of synapses during learning, cannot be written back into the genotype, *Baldwin* [76.127] and *Waddington* [76.128] suggested that learning might indeed affect the evolutionary course in subtle but effective ways. Baldwin's argument was that learning accelerates evolution because suboptimal individuals can reproduce by acquiring during life necessary features for survival. However, variation occurring during successive generation might lead to the discovery of genetic traits that lead to the establishment of the same characteristics that were previously acquired through lifetime learning. This latter aspect of Baldwin's effect, namely indirect genetic assimilation of learned traits, has been later supported by scientific evidence and defined by *Waddington* [76.128] as a canalization effect.

Learning however, also has costs such as: (1) a delay in the ability to acquire fitness (due to the need to develop fit behavior ontogenetically), and (2) increased unreliability due to the fact that the possibility to develop certain abilities ontogenetically is subjected to partially unpredictable characteristics of the robot–environment interaction [76.129]. In the next two subsections we describe two experiments that show some of the potential advantages of combining evolution and learning.

76.8.1 Learning to Adapt to Fast Environmental Variations

Consider the case of a Khepera robot that should explore an arena surrounded by black or white walls to reach a target placed in a randomly selected location [76.126]. Evolving robots are provided with eight sensory neurons that encode the state of the four corresponding infrared sensors and two motor neurons that control the desired speed of the two wheels. Since the color of the walls change every generation and since the color significantly affects the intensity of the response of the infrared sensors, evolving robots should develop an ability to *infer* whether they are currently located in an environment with white or black walls and learn to modify their behavior during lifetime. That is, robots should avoid walls only when the infrared sensors are almost fully activated in the case of arenas with white walls, while they should avoid walls even when the infrared sensors are slightly activated in the case of arenas with black walls.

Robots were provided with a neural controller (Fig. 76.24) including four sensory neurons that encoded the state of four corresponding infrared sensors;

two motor neurons that encoded the desired speed of the two wheels; and two teaching neurons that encoded the teaching values used to modify the connection weights from the sensory neurons to the motor neurons during the robots' lifetime. This special architecture allows evolving robots to transform the sensory states experienced by the robots during their lifetime into teaching signals that might potentially lead to adaptive variations during lifetime. Analysis of evolved robots revealed that they developed two different behaviors that are adapted to the particular arena where they happen to be *born* (surrounded by white or black walls). Evolving robots did not inherit an ability to behave effectively, but rather a predisposition to learn to behave. This predisposition to learn involves several aspects such as a tendency to experience useful learning experiences, a tendency to acquire useful adaptive characters through learning, and a tendency to channel variations toward different directions in different environmental conditions [76.126].

76.8.2 Evolution of Learning

In the previous example, the evolutionary neural network learned using a standard learning rule that was applied to all synaptic connections. *Floreano and Mondada* [76.130] explored the possibility of genetically encoding and evolving the learning rules associated to the different synaptic connections of a neural network embedded in a real robot. The main motivation of this line of work was to evolve robots capable of adapting to a partially unknown environment, rather than robots adapted to the environment(s) seen during evolution. In order to prevent evolutionary tuning of the neural network to the specificities of the evolutionary environment (which would limit transfer to different

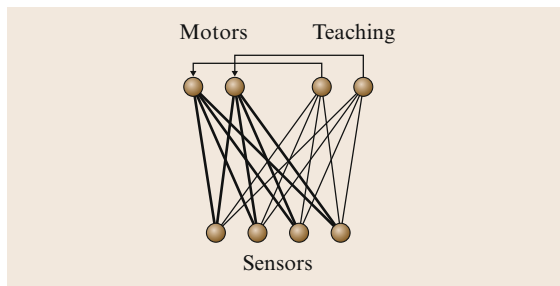


Fig. 76.24 A self-teaching network. The output of the two teaching neurons is used as a teaching value for the two motor neurons. The weights that connect the sensory neurons to the teaching neurons do not vary during the robots' lifetime while the weights that connect the sensory neurons to the motor neurons are modified with an error-correction algorithm

environments or transfer from simulation to reality), the synaptic weight values were not genetically encoded. Instead, each synaptic connection in the network was described by three genes that defined its sign, its learning rule, and its learning rate (Fig. 76.25). Every time a genome was decoded into a neural network and downloaded onto the robot, the synaptic strengths were initialized to small random values and could change according to the genetically specified rules and rates while the robot interacted with the environment. Variations of this methodology included a more compact genetic encoding where the learning properties were associated to a neuron instead of a synapse. All synapses afferent to a neuron used its genetically specified rules and rates. Genes could encode four types of Hebbian learning that were modeled upon neurophysiological data and were complementary to each other [76.131].

Experimental results in a nontrivial, multitask environment (Fig. 76.26, [VIDEO 40](#)) indicated that this methodology has a number of significant advantages with respect to the evolution of synaptic strengths without learning [76.48]. Robots evolved faster and obtained better fitness values. Furthermore, evolved behaviors were qualitatively different, notably in that they did not exploit minimal solutions tuned to the environment (such as turning only on one side, or turning in circles tuned to the dimensions of the evolutionary arena). Most important, these robots displayed remarkable adaptive properties after evolution. Best evolved individuals: (1) transferred perfectly from simulated

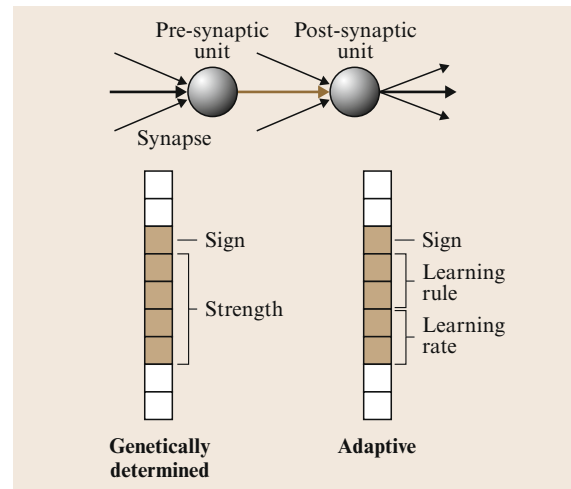


Fig. 76.25 Two methods for genetically encoding a synaptic connection. Genetically determined synapses cannot change during the lifetime of the robot. Adaptive synapses instead are randomly initialized and can change during lifetime of the robot according to the learning rules and rates specified in the genome

to physical robots, (2) accomplished the task when the light and reflection properties of the environment were modified, (3) accomplished the task when key landmarks and target areas of the environment were displaced, and (4) transferred well across morphologically different robotic platforms. In other words, these robots were selected for their ability to solve a partially unknown problem by adapting on the fly, rather than for being a solution to the problem seen during evolution.

In further experiments where the genetic code for each synapse of the network included one gene whose value caused its remaining genes to be interpreted as connection strengths or learning rules and rates, 80% of the synapses *made the choice* of using learning, reinforcing the fact that this genetic strategy has a comparatively stronger adaptive power [76.131]. This methodology could also be used to evolve the morphology of neural controllers where synapses are created at runtime and therefore their strengths cannot be genetically spec-

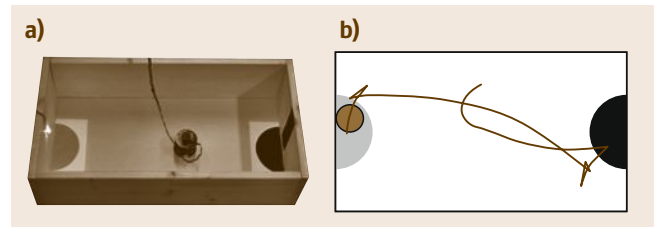


Fig. 76.26 (a) A mobile robot Khepera equipped with a vision module can gain fitness points by staying on the *grey area* only when the light is on. The light is normally off, but it can be switched on if the robot passes over the *black area* positioned on the other side of the arena. The robot can detect ambient light and wall color, but not the color of the floor. (b) Behavior of an individual evolved in simulation with genetic encoding of learning rules

ified [76.132]. Recently, the adaptive properties of this type of adaptive genetic encoding were confirmed also in the context of evolutionary spiking neurons for robot control [76.133].

76.9 Evolution of Social Behavior

In the previous sections, we limited our analysis to individual behaviors, i. e., to the evolution of robots placed in an environment that does not include other robots. The evolutionary method, however, can also be applied to evolve social behaviors in which multiple robots situated in the same environment interact between themselves in cooperative or competitive manners.

As we will see, competitive co-evolution is particularly interesting from the point of view of synthesizing progressively more complex capacities and from the point of view of developing solutions that are robust with respect to environmental variations. Cooperative evolution instead is particularly interesting for the possibility to solve problems that cannot be handled by a single robot, because of physical constraints or limited behavioral capabilities [76.134] and to develop solutions that are robust.

76.9.1 Coevolving Predator and Prey Robots

Competitive coevolution, for example the coevolution of two populations of predator and prey robots that are evolved for the ability to catch prey and to escape predators, respectively, has two characteristics that are particularly interesting from an evolutionary robotics perspective. The first aspect is that the competition between populations with different interests might spontaneously lead to a sort of incremental evolutionary process where evolving individuals are faced with

progressively more complex challenges (although this is not necessarily the case). Indeed, in initial generations the task of the two populations is relatively simple because opponents have simple and poorly developed abilities on average. After a few generations, however, the abilities of the two populations increase and, consequently, the challenges for each population become more difficult. The second aspect consists of the fact that the environment varies across generations because it includes other coevolving individuals. This implies that coevolving individuals should be able to adapt to ever-changing environments and to develop behaviors that are robust with respect to environmental variations [76.135].

The potential advantages of competitive coevolution for evolutionary robotics have been demonstrated by a set of experiments conducted by *Floreano* and *Nolfi* [76.136, 137] where two populations of robots were evolved for the ability to catch prey and escape predators, respectively (Fig. 76.27).

The results indicated that both predator and prey robots tended to vary their behavior throughout generations without converging on a stable strategy. The behavior displayed by individuals at each generation tended to be tightly adapted to the counter-strategy exhibited by the opponent of the same generation (VIDEO 38). This evolutionary dynamic however does not really lead to long-lasting progress because, after an initial evolutionary phase, the coevolutionary

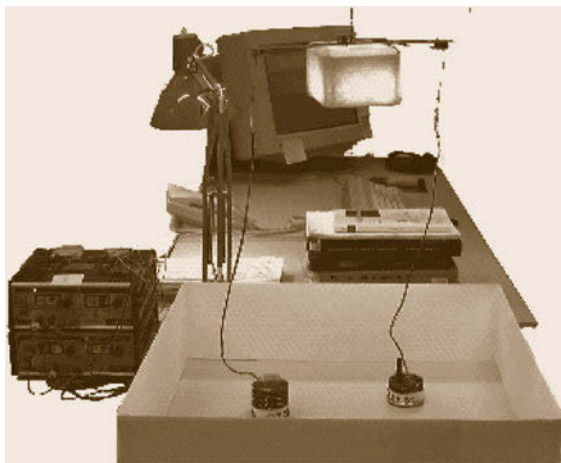


Fig. 76.27 Experimental setup. The predator and prey robot (from left to right) are placed in an arena surrounded by walls and are allowed to interact for several trials starting at different randomly generated orientations. Predators are selected on the basis of the percentage of trials in which they are able to catch (i. e., to touch) the prey, and prey on the basis of the percentage of trials in which they were able to escape (i. e., to not be touched by) predators. Predators have a vision system, whereas the prey have only short-range distance sensors, but can go twice as fast as the predator. Collision between the robots is detected by a conductive belt at the base of the robots

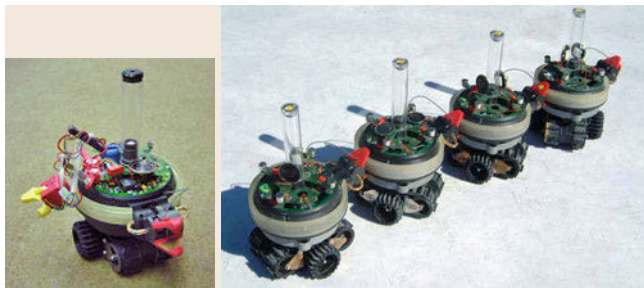


Fig. 76.28 An s-bot and a simulated swarm-bot consisting of four s-bots assembled in chain formation

process led to a limit cycle dynamic where the same small set of behavioral strategies recycled over and over again along generations [76.137]. This limit cycle dynamic can be explained by considering that prey robots tended to vary their behavior in order to disorient predators as soon as predators become effective against the current behavioral strategies exhibited by prey robots.

However, experiments [76.138] where robots were allowed to change their behavior on the fly on the basis of unsupervised Hebbian learning rules showed that

the evolutionary phase where coevolving robots were able to produce real progress was significantly longer, and evolved predators displayed an ability to effectively cope with prey exhibiting different behavioral strategies by adapting their behavior on the fly to the prey's behavior. Prey instead tended to display behavior that changed in unpredictable ways.

Further experiments showed that competitive coevolution can solve problem that the evolution of a single population cannot. *Nolfi and Floreano* [76.137] demonstrated that the attempt to evolve predators robot for the ability to catch a fixed pre-evolved prey produced lower performance with respect to control experiments where predators and prey were coevolved at the same time.

76.9.2 Evolving Cooperative Behavior

As testified by social insects, colonies of simple cooperating individuals can display remarkable capacities and exhibit self-organising behaviors in which the spatio-temporal pattern observed at the system level emerge from numerous interactions among the individual robots. On the other hand, designing collective robotic systems of this sort constitutes a difficult problem due to the indirect relationship between the desired group behavior and the characteristics of the individual robots. By evaluating the robotic system as a whole (i. e., by selecting the robots on the basis of the global behavior that emerge from a large number of robot/environmental and robot/robot interactions), Evolutionary Robotics provides a means for discovering effective behavioral solutions and simple and robust control policies [76.139].

Recent research showed that teams of evolved robots can:

1. Develop robust and effective coordinated behavior [76.140, 141]
2. Collaborate by assuming complementary role [76.141, 142] ([VIDEO 376](#))
3. Display self-organizing properties [76.143]
4. Develop and use communicative capabilities [76.144–146].

Moreover, some of the research carried in this area demonstrated how evolutionary robotics experiments can contribute to model biological phenomena, e.g., to identify the evolutionary conditions that enable the emergence of cooperative communicative behaviors [76.146] or the mechanisms enabling the evolution of effective division of labour strategies [76.147]

Here we briefly review a series of experiments where swarm-bots [76.148], i. e., groups of autonomous robots capable of assembling by physically connecting together, were evolved for the ability to display coordinated motion ( VIDEO 115). Each individual robot consisted of a main platform (chassis) and turret that could actively rotate with respect to each other (Fig. 76.28). The chassis included tracks with teathed wheels for navigation on both rough and flat terrain, and infrared sensors pointing to the ground. The turret included a gripper, sixteen light-sensors distributed around the body, a loudspeaker, three microphones, and a traction sensor placed between the turret and the chassis to detect the direction and the intensity of the traction force that the turret exerts on the chassis. Swarm-bots were formed by several robots provided with identical neural controllers and assembled together so to form a single physical entity.

By evolving the neural controllers of these Swarm-bots, Baldassare et al. [76.140] demonstrated how the robots can display a robust and effective coordinated capacities that allow the individuals to negotiate and converge on a coherent direction and to keep moving along that direction by compensating the disalignments originating during motion. Such behavioral capacity was robust enough to allow a smooth transfer from simulation to reality and to allow the robots to generalize their capacity to rugged terrains. In an extended experiments in which the s-bots were also equipped with infrared sensors, speakers and microphones, the evolved swarm-bots also showed a capacity to avoid dangers (e.g., holes) by coordinately changing direction as soon as one s-bot detected a hole [76.149].

Evolved swarm-bots generalized their coordinated motion capabilities also when they were tested in different conditions (e.g., when they were assembled in much more numerous groups and/or in different topologies, or when they had to also carry heavy objects by pushing and pulling them in a coordinated manner). Finally, when placed in new environmental conditions (e.g., in environment with obstacle and walls), the swarm-bots spontaneously displayed new behavioral skills (related to acquired skills), such as the ability to cooperatively avoid obstacles, without any further adaptation. This ability to display new related behaviors, in new behavioral conditions, emerged as a result of the dynamical process originating from the interaction of the same robots with the new environmental conditions [76.142, 150].

76.9.3 Evolution of Communication

Communication represents a key aspect in collective behaviors. Recent research in evolutionary robotics has demonstrated how sophisticated communication capabilities can emerge and evolve in population of robots selected for the ability to perform tasks requiring coordination and/or cooperation.

The analysis of these experiments indicate that communicative interactions often originate as the result of cues, that provide useful information to other robots, produced inadvertently during the execution of specific behaviors [76.146, 151]. The presence of these cues create the basis for the development of an ability to react to them in an adaptive way thus leading to the establishment of adaptive communicative interactions in which robots produce signals and react to detected signals adaptively. The establishment of these forms of communicative interactions then create the adaptive conditions for the co-evolution of signalling and response strategies [76.152] ( VIDEO 117).

The reliability and stability of the resulting communication system depend on the level of relatedness (i. e., genetic similarity) between robots and the level at which they were selected [76.146]. Robots that are genetically highly related or that are selected on the basis of the behavior exhibited by the group evolve reliable signals and stable communicative conventions. In contrast, when relatedness between robots is low and selection is acting at the level of the individuals, the evolutionary process might lead to the emergence of instable, ineffective and in some case deceptive communication forms [76.153, 154].

The evolution of communication is strongly interlinked with the evolution of other behavioral capacities [76.155]. Indeed, after all, robots need to develop appropriate behaviors to access and/or generate the information to be communicated and/or to react to detected signals appropriately. The co-adaptation of behavioral and communicative skills might lead to prolonged innovation phases in which the development of behavioral capacities create the adaptive conditions for the development of communication capacities and vice versa [76.151, 152]. Moreover, the co-adaptation of behavioral and communication capacities tend to lead to highly contingent evolutionary processes in which the capacities possessed by the population at a certain evolutionary phase strongly influence the outcome of the successive phases [76.152, 156] ( VIDEO 117).

76.10 Evolutionary Hardware

In recent years, technology advancements have allowed researchers to explore evolution of electronic circuits. In this section, we briefly summarize some foundational work in this direction.

76.10.1 Evolvable Hardware Robot Controllers

In most of the work discussed so far some form of genetically specified neural network, implemented in software, has been at the center of the robot control system. Work on a related approach of evolving control systems directly onto hardware dates back to *Thompson's* work in the mid 1990s [76.157]. In contrast to hardware controllers that are designed or programmed to follow a well-defined sequence of instructions, evolved hardware controllers are directly configured by evolution and then allowed to behave in real time according to semiconductor physics. By removing standard electronics design constraints, the physics can be exploited to produce highly nonstandard and often very efficient and minimal systems [76.158].

Thompson [76.157] used artificial evolution to design an onboard hardware controller for a two-wheeled autonomous mobile robot engaged in simple wall-avoidance behavior in an empty arena. Starting from a random orientation, and position near the wall, the robot had to move to the center of the arena and stay

there using limited sensory input (Fig. 76.29). The direct current (DC) motors driving the wheels were not allowed to run in reverse and the robot's only sensors were a pair of time-of-flight sonars rigidly mounted on the robot, pointing left and right.

Thompson's approach made use of a so-called dynamic state machine (DSM) – a kind of generalized read-only memory (ROM) implementation of a finite-state machine where the usual constraint of strict synchronization of input signals and state transitions are relaxed (in fact put under evolutionary control). The system had access to a global clock whose frequency was also under genetic control. Thus evolution determined whether each signal was synchronized to the clock or allowed to flow asynchronously. This allowed the evolving DSM to be tightly coupled to the dynamics of interaction between the robot and environment and for evolution to explore a wide range of systems dynamics. The process took place within the robot in a kind of *virtual reality* in the sense that the real evolving hardware controlled the real motors, but the wheels were just spinning in the air. The movements that the robot would have actually performed if the wheels had been supporting it were then simulated and the sonar echo signals that the robot was expected to receive were supplied in real time to the hardware DSM. Excellent performance was attained after 35 generations, with good transfer from the virtual environment to the real world (Fig. 76.29).

Shortly after this research was performed, particular types of field programmable gate arrays (FPGAs) which were appropriate for evolutionary applications became available. FPGAs are reconfigurable systems allowing the construction of circuits built from basic logic elements. Thompson exploited their properties to demonstrate evolution directly in the chip. By again relaxing standard constraints, such as synchronizing all elements with a central clock, he was able to develop very novel forms of functional circuits, including a controller for a Khepera robot using infrared sensors to avoid obstacles [76.158, 159].

Following Thompson's pioneering work, *Keymeulen* et al. evolved a robot control system using a Boolean function approach implemented on gate-level evolvable hardware [76.160]. This system acted as a navigation system for a mobile robot capable of locating and reaching a colored ball while avoiding obstacles. The robot was equipped with infrared sensors and an vision system giving the direction and distance to the target. A programmable logic device (PLD) was

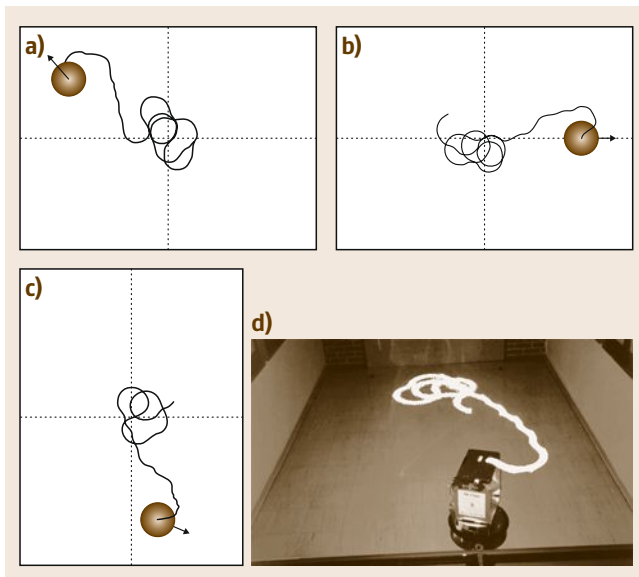


Fig.76.29a-d Wall-avoidance behavior of a robot with an evolved hardware controller in virtual reality (a-c) and the real world (d)

used to implement a Boolean function in its disjunctive form. This work demonstrated that such gate-level evolvable hardware was able to take advantage of the correlations in the input states and to exhibit useful generalization abilities, thus allowing the evolution of robust behavior in simulation followed by a good transfer into the real world.

In a rather different approach, *Ritter et al.* used an FPGA implementation of an onboard evolutionary algorithm to develop a controller for a hexapod

robot [76.161]. *Roggen et al.* devised a multicellular reconfigurable circuit capable of evolution, self-repair, and adaptation [76.162], and used it as a substrate for evolving spiking controllers of a wheeled robot [76.163]. Although evolved hardware controllers are not widely used in evolutionary robotics, they still hold out the promise of some very useful properties, such as robustness to faults, which make them interesting for extreme condition applications such as space robotics.

76.11 Closing Remarks

Evolutionary robotics is a young and integrated approach to robot development without human intervention where machines change and adapt by capitalizing on the interactions with their environment. Despite initial skepticism by mainstream and applied robotics practitioners and even by pioneers of this approach [76.164], over the years the field has been constantly growing with new methods and approaches for evolving more complex, efficient, and sometimes surprising robotic systems. In some areas, such as morphology and self-assembly, evolutionary robotics is still the most widely used and powerful approach.

Evolutionary robotics is not only a method for automatic robot development inspired by biology, but

also a tool for investigating open questions in biology concerning evolutionary, developmental, and brain dynamics. Its richness and fecundity make us believe that this approach will continue to grow and progress towards the creation of a new species of machines capable of self-evolution.

To gain a practical knowledge, interested readers might use software libraries such as framework for autonomous robotics simulation and analysis (*FARSA*) [76.165], an open-software tool that permit to carry on evolutionary robotics experiments based on a variety of robotic platforms and to replicate and vary some of the experiments described in this chapter [76.166].

Video-References

-  **VIDEO 36** Visual navigation of mobile robot with pan-tilt camera
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/36>
-  **VIDEO 37** Visual navigation with collision avoidance
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/37>
-  **VIDEO 38** Coevolved predator and prey robots
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/38>
-  **VIDEO 39** Evolution of collision-free navigation
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/39>
-  **VIDEO 40** Online learning to adapt to fast environmental variations
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/40>
-  **VIDEO 41** iCub language comprehension
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/41>
-  **VIDEO 114** Resilient machines through continuous self-modeling
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/114>
-  **VIDEO 115** A swarm-bot of eight robots displaying coordinated motion
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/115>
-  **VIDEO 116** Discrimination of objects through sensory-motor coordination
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/116>
-  **VIDEO 117** Evolution of cooperative and communicative behaviors
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/117>
-  **VIDEO 118** Exploration and homing for battery recharge
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/118>

-  VIDEO 119 Introduction to evolutionary robotics at EPFL
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/119>
-  VIDEO 371 Evolution of visually guided behavior on Sussex gantry robot
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/371>
-  VIDEO 372 Evolved walking in an Octpod
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/372>
-  VIDEO 373 Evolved homing walk on rough ground
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/373>
-  VIDEO 374 Evolved bipedal walking
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/374>
-  VIDEO 375 Evolved GasNet visualization
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/375>
-  VIDEO 376 Evolved group coordination
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/376>
-  VIDEO 771 Morphological change in an autonomous robot
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/771>
-  VIDEO 772 More complex robots evolve in more complex environments
available from <http://handbookofrobotics.org/view-chapter/76/videodetails/772>

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77. Neurorobotics: From Vision to Action

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The lay view of a robot is a mechanical human, and thus robotics has always been inspired by attempts to emulate biology. In this chapter, we extend this biological motivation from humans to animals more generally, but with a focus on the central nervous systems in its relationship to the bodies of these creatures. In particular, we investigate the sensorimotor loop in the execution of sophisticated behavior. Some of these sections concentrate on cases where vision provides key sensory data. Neuroethology is the study of the brain mechanisms underlying animal behavior, and Sect. 77.2 exemplifies the lessons it has to offer robotics by looking at optic flow in bees, visually guided behavior in frogs, and navigation in rats, turning then to the coordination of behaviors and the role of attention. Brains are composed of diverse subsystems, many of which are relevant to robotics, but we have chosen just two regions of the mammalian brain for detailed analysis. Section 77.3 presents the cerebellum. While we can plan and execute actions without a cerebellum, the actions are no longer graceful and become uncoordinated. We reveal how a cerebellum can provide a key ingredient in an adaptive control system, tuning parameters both within and between motor schemas. Section 77.4 turns to the mirror system, which provides shared representations which bridge between the execution of an action and the observation of that action when performed by others. We develop a neurobiological model of how learning may forge mirror neurons for hand movements, provide a Bayesian view of

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a robot mirror system, and discuss what must be added to a mirror system to support robot imitation. We conclude by emphasizing that, while neuroscience can inspire novel robotic designs, it is also the case that robots can be used as embodied test beds for the analysis of brain models.

77.1 Definitions and History

Neurorobotics may be defined as:

the design of computational structures for robots inspired by the study of the nervous systems of humans and other animals.

We note the success of (deep) *artificial* neural networks – networks of simple computing elements whose connections change with *experience* – as providing a medium for parallel adaptive computation that has seen application in robot vision systems and controllers but here we emphasize neural networks derived from the study of specific *neurobiological* systems. Neurorobotics has a twofold aim: creating better machines which employ the principles of natural neural computation; and using the study of bio-inspired robots to improve understanding of the functioning of the brain. Chapter 75, *Biologically Inspired Robots*, complements our study of *brain design* with work on *body design*, the design of robotic control and actuator systems based on careful study of the relevant biology.

77.1.1 History and Definitions

Science has long been playing with technical replicas of biological behavior. As a famous example, *Walter* [77.1] described two *biologically inspired* robots, the electromechanical tortoises *Machina speculatrix* and *M. docilis* (though each body has wheels, not legs). *M. speculatrix* has a steerable photoelectric cell, which makes it sensitive to light, and an electrical contact, which allows it to respond when it bumps into obstacles. The photoreceptor rotates until a light of moderate intensity is registered, at which time the organism orients itself towards the light and approaches it. However, very bright lights, material obstacles, and steep gradients are repellent to the *tortoise*. The latter stimuli convert the photoamplifier into an oscillator, which causes alternating movements of butting and withdrawal, so that the robot pushes small objects out of its way, goes around heavy ones, and avoids slopes. The *tortoise* has a *hutch*, which contains a bright light. When the machine's batteries are charged, this bright light is repellent. When the batteries are low, the light becomes attractive to the machine and the light continues to exert an attraction until the tortoise enters the hutch, where the machine's circuitry is temporarily turned off until the batteries are recharged, at which time the bright hutch light again exerts a negative tropism. The second robot, *M. docilis* was produced by grafting onto *M. speculatrix* a circuit designed to

form conditioned reflexes. In one experiment, Walter connected this circuit to the obstacle-avoiding device in *M. speculatrix*. Training consisted of blowing a whistle just before bumping the shell.

Although Walter's controllers are simple and not based on neural analysis, they do illustrate an attempt to gain inspiration from seeking the simplest mechanisms that will yield an interesting class of biologically inspired robot behaviors, and then showing how different additional mechanisms yield a variety of enriched behaviors. *Braitenberg's* book [77.2] is very much in this spirit and has entered the canon of neurorobotics. While their work provides a historical background for the studies surveyed here, we instead emphasize studies inspired by the computational neuroscience of the mechanisms serving vision and action in the human and in animal brains. We seek lessons from linking behavior to the analysis of the internal workings of the brain (1) at the relatively high level of characterizing the functional roles of specific brain regions (or the functional units of analysis called schemas, Sect. 77.2.4), and the behaviors which emerge from the interactions between them, and (2) at the more detailed level of models of neural circuitry linked to the data of neuroanatomy and neurophysiology. There are lessons for neurorobotics to be learned from even finer-scale analysis of the biophysics of individual neurons and the neurochemistry of synaptic plasticity, but these are beyond the scope of this chapter (see *Segev and London* [77.3] and *Fregnac* [77.4], respectively, for entry points into the relevant computational neuroscience).

The plan of this chapter is as follows. We will start with explaining how the higher-level *cognitive* functionality of vision-based planning and navigation is realized in biology, and how this relates to robotic systems (Sect. 77.2). We then (Sect. 77.3) explain vertebrate movement generation itself, and put forth a theory on what role the cerebellum plays in tuning and coordinating actions. This is followed by a section on the mirror system and its roles in action recognition and imitation (Sect. 77.4). The introduction will then invite readers to explore the many other areas in which neurorobotics offers lessons from neuroscience to the development of novel robot designs. What follows, then, can be seen as a contribution to the continuing dialog between robot behavior and animal and human behavior in which particular emphasis is placed on the search for the neural underpinnings of vision, visually guided action, and cerebellar control.

77.2 The Case for Vision

Before we turn to vertebrate brains for much of our inspiration for neurorobotics, we briefly sample the rich literature on insect-inspired research. Among the founding studies in computational neuroethology were a series of reports from the laboratory of Werner Reichardt in Tübingen, which linked the delicate anatomy of the fly's brain to the extraction of visual data needed for flight control. More than 40 years ago, Reichardt [77.5] published a model of motion detection inspired by this work that has long been central to discussions of visual motion in both the neuroscience and robotics literatures. Borst and Dickinson [77.6] provide a recent study of continuing biological research on visual course control in flies. Such work has inspired a large number of robot studies, including those of van der Smagt and Groen [77.7], van der Smagt [77.8], Liu and Usseglio-Viretta [77.9], Ruffier et al. [77.10], and Reiser and Dickinson [77.11].

77.2.1 Optic Flow in Bees and Robots

Here, however, we look in a little more detail at honeybees. Srinivasan et al. [77.15] continued the tradition of studying image motion cues in insects by investigating how optic flow (the flow of pattern across the eye induced by motion relative to the environment) is exploited by honeybees to guide locomotion and navigation. They analyzed how bees perform a smooth

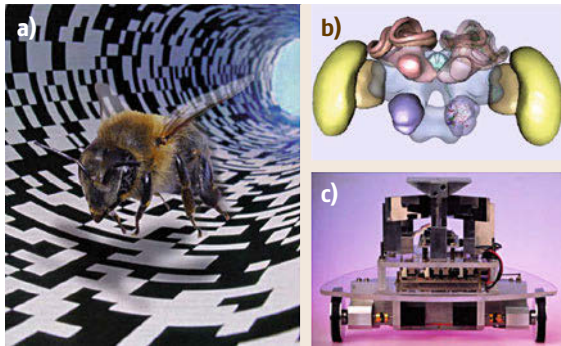


Fig. 77.1 (a) Observation of the trajectories of honeybees flying in visually textured tunnels has provided insights into how bees use optic flow cues to regulate flight speed and estimate distance flown, and balance optic flow in the two eyes to fly safely through narrow gaps (images courtesy of Srinivasan et al. [77.12]). This information has been used to build autonomously navigating robots. (b) Schematic illustration of a honeybee brain, carrying about a million neurons within $\approx 1 \text{ mm}^3$ (after [77.13]). (c) A mobile robot guided by an optic flow algorithm based on the studies exemplified in [77.14]

landing on a flat surface: image velocity is held constant as the surface is approached, thus automatically ensuring that flight speed is close to zero at touchdown. This obviates any need for explicit knowledge of flight speed or height above the *ground*. This landing strategy was then implemented in a robotic gantry to test its applicability to autonomous airborne vehicles. Barron and Srinivasan [77.14] investigated the extent to which ground speed is affected by headwinds. Honeybees were trained to enter a tunnel to forage at a sucrose feeder placed at its far end (Fig. 77.1a). The bees used visual cues to maintain their ground speed by adjusting their airspeed to maintain a constant rate of optic flow, even against headwinds which were, at their strongest, 50% of a bee's maximum recorded forward velocity.

Vladusich et al. [77.16] studied the effect of adding goal-defining landmarks. Bees were trained to forage in an optic-flow-rich tunnel with a landmark positioned directly above the feeder. They searched much more accurately when both odometric and landmark cues were available than when only odometry was available. When the two cue sources were set in conflict, by shifting the position of the landmark in the tunnel during tests, bees overwhelmingly used landmark cues rather than odometry. This, together with other such experiments, suggests that bees can make use of odometric and landmark cues in a more flexible and dynamic way than previously envisaged. In earlier studies of bees flying down a tunnel, Srinivasan and Zhang [77.17] placed different patterns on the left and right walls. They found that bees balance the image velocities in the left and right visual fields. This strategy ensures that bees fly down the middle of the tunnel, without bumping into the side walls, enabling them to negotiate narrow passages or to fly between obstacles. This strategy has been applied to a corridor-following robot (Fig. 77.1c). By holding constant the average image velocity as seen by the two eyes during flight, the bee avoids potential collisions, slowing down when it flies through a narrow passage. The movement-sensitive mechanisms underlying these various behaviors differ qualitatively as well as quantitatively, from those that mediate the optomotor response (e.g., turning to track a pattern of moving stripes) that had been the initial target of investigation of the Reichardt laboratory. The lesson for robot control is that flight appears to be coordinated by a number of visuomotor systems acting in concert, and the same lesson can apply to a whole range of tasks that must convert vision to action. Of *course*, vision is but one of the sensory systems that play a vital role in insect behavior. Webb [77.18] uses her own work on robot

design inspired by the auditory control of behavior in crickets to anchor a far-ranging assessment of the extent to which robotics can offer good models of animal behaviors.

77.2.2 Visually Guided Behavior in Frogs and Robots

Lettvin et al. [77.19] treated the frog's visual system from an ethological perspective, analyzing circuitry in relation to the animal's ecological niche to show that different cells in the retina and the visual midbrain region known as the tectum were specialized for detecting predators and prey. However, in much visually guided behavior, the animal does not respond to a single stimulus, but rather to some property of the overall configuration. We thus turn to the question *what does the frog's eye tell the frog?*, stressing the embodied nervous system or, perhaps equivalently, an action-oriented view of perception. Consider, for example, the snapping behavior of frogs confronted with one or more fly-like stimuli. Ingle [77.20] found that it is only in a restricted region around the head of a frog that the presence of a fly-like stimulus elicits a snap, that is, the frog turns so that its midline is pointed at the stimulus and then lunges forward and captures the prey with its tongue. There is a larger zone in which the frog merely orients towards the target, and beyond that zone the stimulus elicits no response at all. When confronted with two flies within the snapping zone, either of which is vigorous enough that it could elicit a snapping response alone, the frog exhibits one of three reactions: it snaps at one of the flies, it does not snap at all, or it snaps in between at the *average fly*. Didday [77.21] offered a simple model of this choice behavior which may be considered as the prototype for a *winner-take-all* (WTA) model, which receives a variety of inputs and (under ideal circumstances) suppresses the representation of all but one of them; the one that remains is the *winner* that will play the decisive role in further processing. This was the beginning of *Rana computatrix* (see Arbib [77.22, 23] for overviews).

Studies on frog brains and behavior inspired the successful use of potential fields for robot navigation strategies. Data on the strategies used by frogs to capture prey while avoiding static obstacles (Collett [77.24]) grounded the model by Arbib and House [77.25], which linked systems for depth perception to the creation of spatial maps of both prey and barriers. In one version of their model, they represented the map of prey by a potential field with long-range attraction and the map of barriers by a potential field with short-range repulsion, and showed that summation of these fields yielded a field that could guide the frog's de-

tour around the barrier to catch its prey. Corbacho and Arbib [77.26] later explored a possible role for learning in this behavior. Their model incorporated learning in the weights between the various potential fields to enable adaptation over trials as observed in the real animals. The success of the models indicated that frogs use reactive strategies to avoid obstacles while moving to a goal, rather than employing a planning or cognitive system. Other work, Cobas and Arbib [77.27], studied how the frog's ability to catch prey and avoid obstacles was integrated with its ability to escape from predators. These models stressed the interaction of the tectum with a variety of other brain regions such as the pretectum (for detecting predators) and the tegmentum (for implementing motor commands for approach or avoidance).

Arkin [77.28] showed how to combine a computer vision system with a frog-inspired potential field controller to create a control system for a mobile robot that *could* successfully navigate in a fairly structured environment using camera input. The resultant system thus enriched other roughly contemporaneous applications of potential fields in path planning with obstacle avoidance for both manipulators and mobile robots (Khatib [77.29], Krogh and Thorpe [77.30]). The work on *Rana computatrix* proceeded at two levels – both biologically realistic neural networks and in terms of functional units called *schemas*, which compete and cooperate to determine behavior. Section 77.2.4 will show how more general behaviors can emerge from the competition and cooperation of perceptual and motor schemas, as well as more abstract coordinating schemas. Such ideas were, of course, developed independently by a number of authors, and so entered the robotics literature by various routes, of which the best known may be the subsumption architecture of Brooks [77.31] and the ideas of Braitenberg cited above, whereas Arkin's work on behavior-based robotics [77.32] is, indeed, rooted in schema theory. Arkin et al. [77.33] present a recent example of the continuing interaction between robotics and ethology, offering a novel method for creating high-fidelity models of animal behavior for use in robotic systems based on a behavioral systems approach (i. e., based on a schema-level model of animal behavior, rather than analysis of biological circuits in animal brains), and describe how an ethological model of a domestic dog can be implemented with AIBO, the Sony entertainment robot.

77.2.3 Navigation in Rat and Robot

The tectum, the midbrain visual system which determines how the frog turns its whole body towards its prey or orients it for escape from predators (Sect. 77.2.2), is

homologous with the superior colliculus of the mammalian midbrain. The rat superior colliculus has been shown to be *frog like*, mediating approach and avoidance (Dean et al. [77.34]), whereas the best-studied role of the superior colliculus of cat, monkey, and human is in the control of saccades, rapid eye movements to acquire a visual target. Moreover, the superior colliculus can integrate auditory and somatosensory information into its visual frame (Stein and Meredith [77.35]), and this inspired Strosslin et al. [77.36] to use a biologically inspired approach based on the properties of neurons in the superior colliculus to learn the relation between visual and tactile information in control of a mobile robot platform. More generally, then, the comparative study of mammalian brains has yielded a rich variety of computational models of importance in neurobotics. In this section, we further introduce the study of *mammalian neurobotics* by looking at studies of mechanisms of the rat brain for spatial navigation.

The frog's detour behavior is an example of what O'Keefe and Nadel [77.37] called the *taxon* (*behavioral orientation*) system (as in Braitenberg, [77.38] a *taxis* (plural *taxes*) is an organism's response to a stimulus by movement in a particular direction). They distinguished this from a system for *map-based navigation* and proposed that the latter resides in the hippocampus, though Guazzelli et al. [77.39] qualified this assertion, showing how the hippocampus may function as *part of* a cognitive map. The *taxon* versus *map* distinction is akin to the distinction between reactive and deliberative control in robotics (Arkin et al. [77.33]). It will be useful to relate *taxis* to the notion of an *affordance* (Gibson [77.40]), a feature of an object or environment relevant to action, for example, in picking up an apple or a ball, the identity of the object may be irrelevant, but the size of the object is crucial. Similarly, if we wish to push a toy car, recognizing the make of car copied in the toy is irrelevant, whereas it is crucial to recognize the placement of the wheels to extract the direction in which the car can be readily pushed. Just as a rat may have basic *taxes* for approaching food or avoiding a bright light, say, so does it have a wider repertoire of affordances for possible actions associated with the immediate sensing of its environment. Such affordances include *go straight ahead* for visual sighting of a corridor, *hide* for a dark hole, *eat* for food as sensed generically, *drink* similarly, and the various turns afforded by, e.g., the sight of the end of the corridor. It also makes rich use of olfactory cues. In the same way, a robot's behavior will rely on a host of reactions to local conditions in fulfilling a plan, e.g., knowing that it must go to the end of a corridor it will nonetheless use local visual cues to avoid hitting obstacles or to determine through which angle to turn when reaching a bend in the corridor.

Both normal and hippocampal-lesioned rats can learn to solve a simple T-maze (e.g., learning whether to turn left or right to find food) in the absence of any consistent environmental cues other than the T-shape of the maze. If anything, the lesioned animals learn this problem faster than normal ones. After the criterion was reached, probe trials with an eight-arm radial maze were interspersed with the usual T-trials. Animals from both groups consistently chose the side to which they were trained on the T-maze. However, many did not choose the 90° arm but preferred either the 45° or 135° arm, suggesting that the rats eventually solved the T-maze by learning to rotate within an ego-centric orientation system at the choice point through *approximately* 90°. This leads to the hypothesis of an *orientation vector* being stored in the animal's brain but does not tell us where or how the orientation vector is stored. One possible model would employ coarse coding in a linear array of cells, coding for turns from -180° to +180°. From the behavior, one might expect that only the cells close to the preferred *behavioral* direction are excited, and that learning *marches* this peak from the old to the new preferred direction. To *unlearn* -90°, say, the array must reduce the peak there, while at the same time *building* a new peak at the new direction of +90°. If the old peak has *massp(t)* and the new peak has *massq(t)*, then as *p(t)* declines toward 0 while *q(t)* increases steadily from 0, the center of mass will progress from -90° to +90°, fitting the behavioral data.

The determination of movement direction was modeled by *rat-ification* of the *Arbib* and *House* [77.25] model of frog detour behavior. There, prey was represented by excitation coarsely coded across a population, while barriers were encoded by inhibition whose extent closely matched the retinotopic extent of each barrier. The sum of excitation was passed through a winner-takes-all circuit to yield the choice of movement direction. As a result, the direction of the gap closest to the prey, rather than the direction of the prey itself, was often chosen for the frog's initial movement. The same model serves for behavioral orientation once we replace the direction of the prey (frog) by the direction of the orientation vector (rat), while the barriers correspond to the presence of walls rather than alley ways.

To approach the issue of how a cognitive map can extend the capability of the affordance system, Guazzelli et al. [77.39] extended the *Lieblisch* and *Arbib* [77.41] approach to building a cognitive map as a *world graph*, a set of nodes connected by a set of edges, where the nodes represent recognized places or situations, and the links represent ways of moving from one situation to another. A crucial notion is that a place encountered in different circumstances may be repre-

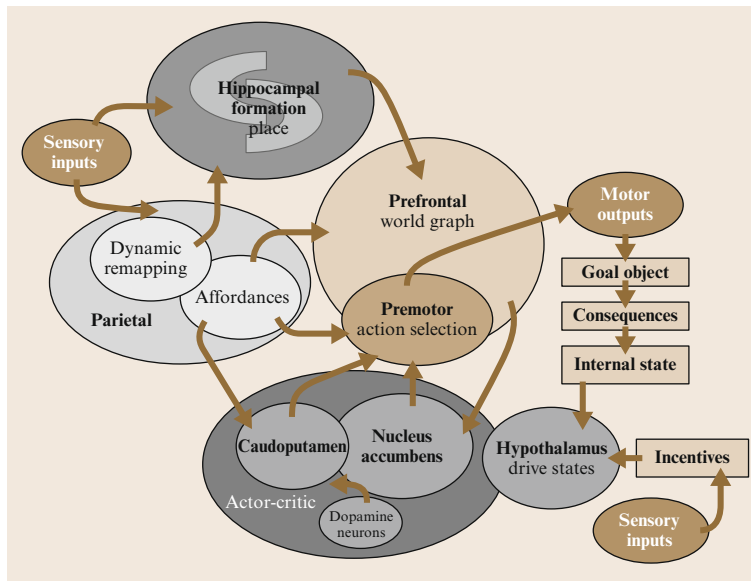


Fig. 77.2 The TAM-WG model has at its basis a system, TAM (the taxon affordance model), for exploiting affordances. This is elaborated by a system, WG (the world graph), which can use a cognitive map to plan paths to targets which are not currently visible. Note that the model processes two different kinds of sensory inputs. At the *bottom right* are those associated with, e.g., hypothalamic systems for feeding and drinking and that may provide both incentives and rewards for the animal's behavior, contributing both to behavioral choices, and to the reinforcement of certain patterns of behavior. The nucleus accumbens and caudoputamen mediate an actor-critic style of reinforcement learning based on the hypothalamic drive of the dopamine system. The sensory inputs at the *top left* are those that allow the animal to sense its relation with the external world, determining both where it is (the hippocampal place system), as well as the affordances for action (the parietal recognition of affordances can shape the premotor selection of an action). The TAM model focuses on the parietal–premotor reaction to immediate affordances; the WG model places action selection within the wider context of a cognitive map (after Guazzelli et al. [77.39])

sented by multiple nodes, but that these nodes may be merged when the similarity between these circumstances is recognized. They model the process whereby the animal decides where to move next, on the basis of its current drive state (hunger, thirst, fear, etc.). The emphasis is on spatial maps for guiding locomotion into regions not necessarily currently visible, rather than retinotopic representations of immediately visible space, and yields exploration and latent learning without the introduction of an explicit exploratory drive. The model shows:

1. How a route, possibly of many steps, may be chosen that leads to the desired goal.
2. How short cuts may be chosen.
3. Through its account of node merging why, in open fields, place cell firing does not seem to depend on direction.

The overall structure and general mode of operation of the complete model is shown in Fig. 77.2, which gives a vivid sense of the lessons to be learned by studying not only specific systems of the mammalian brain

but also their patterns of large-scale interaction. This model is but one of many inspired by the data on the role of the hippocampus and other regions in rat navigation. Here, we just mention as pointers the wider literature the papers by Girard et al. [77.42] and Meyer et al. [77.43], which are part of the *Psikharpax* project, which does for rats what *Rana computatrix* did for frogs and toads.

77.2.4 Salience and Visual Attention

Discussions of how an animal (or robot) grasps an object assume that the animal or robot is attending to the relevant object. Thus, whatever the subtlety of processing in the canonical and mirror systems for grasping, its success rests on the availability of a visual system coupled to an oculomotor control system that bring foveal vision to bear on objects to set the parameters needed for successful interaction. Indeed, the general point is that attention greatly reduces the processing load for animal and robot. The catch, of course, is that reducing the computing load is a Pyrrhic victory unless

the moving focus of attention captures those aspects of behavior that are relevant for the current task – or supports necessary *priority interrupts*. Indeed, directing attention appropriately is a topic for which there is a great richness of both neurophysiological data and robotic application (see *Deco and Rolls* [77.44] and *Choi et al.* [77.45]).

In their neuromorphic model of the bottom-up guidance of attention in primates, *Itti and Koch* [77.46] decompose the input video stream into eight feature channels at six spatial scales. After surround suppression, only a sparse number of locations remain active in each map, and all maps are combined into a unique *saliency map*. This map is scanned by the focus of attention in order of decreasing saliency through the interaction between a winner-takes-all mechanism (which selects the most salient location) and an *inhibition-of-return* mechanism (which transiently suppresses recently attended locations from the saliency map). Because it includes a detailed low-level vision front-end, the model has been applied not only to laboratory stimuli, but also to a wide variety of natural scenes, predicting a wealth of data from psychophysical experiments.

When specific objects are searched for, low-level visual processing can be biased both by the gist (e.g., *outdoor suburban scene*) and also for the features of that object. This top-down modulation of bottom-up processing results in an ability to guide search towards targets of interest (*Wolfe* [77.47]). Task affects eye movements (*Yarbus* [77.48]), as do training and general expertise. *Navalpakkam and Itti* [77.49] propose a computational model which emphasizes four aspects that are important in biological vision: determining the task relevance of an entity, biasing attention for the low-level visual features of desired targets, recognizing these targets using the same low-level features, and incrementally building a visual map of task relevance

at every scene location. It attends to the most salient location in the scene, and attempts to recognize the attended object through hierarchical matching against object representations stored in long-term memory. It updates its working memory with the task relevance of the recognized entity and updates a topographic task-relevance map with the location and relevance of the recognized entity; for example, in one task the model forms a map of likely locations of cars from a video clip filmed while driving on a highway. Such work illustrates the continuing interaction between models based on visual neurophysiology and human psychophysics with the tackling of practical robotic applications.

Orabona et al. [77.50] implemented an extension of the Itti–Koch model on a humanoid robot with moving eyes, using log-polar vision as in *Sandini and Tagliasco* [77.51], and changing the feature construction pyramid by considering proto-object elements (blob-like structures rather than edges). The inhibition-of-return mechanism has to take into account a moving frame of reference, the resolution of the fovea is very different from that at the periphery of the visual field, and head and body movements need to be stabilized. The control of movement might thus have a relationship with the structure and development of the attention system. *Rizzolatti et al.* [77.52] proposed a role for the feedback projections from premotor cortex to the parietal lobe, assuming that they form a tuning signal that dynamically changes visual perception. In practice, this can be seen as an implicit attention system that *selects* sensory information while the action is being prepared and subsequently executed (*Flanagan and Johansson* [77.53], *Flanagan et al.* [77.54], and *Mataric and Pomplun* [77.55]). The early responses, before action onset, of many premotor and parietal neurons suggest a premotor mechanism of attention that deserves exploration in further work in neurorobotics.

77.3 Vertebrate Motor Control

The body of literature on primate motor control is, of course, vast, and gives a patchy view on the principles behind it. Getting a clear view of how limb and general body control functions is difficult; moreover, there are no clear proofs of whether any of the existing views on motor control are correct.

But there exist a few observations of the human central and peripheral nervous systems from which clear conclusions can be drawn. The first observation is the presence of neural communication delays. How does the system know the position of limbs? There are two principled methods: (1) through proprioceptive signals, consisting of muscle spindles and Golgi tendon or-

gans (GOs); and (2) through skin information. It is, however, not very likely that information from muscle spindles and GOs are accurate enough to code limb position. Tendon organs are sensitive to forces along in-series motor units and there is no physiological evidence that Golgi tendon organs signal muscle length (but, of course, force changes with muscle length, so during movement a correlation is found). There is another problem with respect to limb position, which is particularly clear for fingers: flexibilities and nonlinear relationships between finger position and muscle force, in combination with the imprecise receptors, makes the relationship between GO/spindle data and finger posi-

Table 77.1 Classification of sensory fibers from muscle (after [77.56])

Type	Receptor	Axon diameter [μm]	Transmission speed [m/s]	Sensitive to
Ia	Primary spindle endings	12–20	60–100	Muscle length and rate of change
Ib	Golgi tendon organs	12–20	60–100	Muscle tension
II	Secondary spindle endings	6–12	30–70	Muscle length
III	Free nerve endings	2–6	10–30	Skin signals

tion too complex and variable to be a likely candidate to code finger position; after all, the sensors are in the forearm rather than in the fingers; and information on finger position is not available in muscle movement or tendon force. Furthermore, muscle spindle data is noisy [77.57]. It has conversely been shown [77.58, 59] that the receptors in hairy skin code information that can be related to finger position; furthermore, similar data have been found for the knee joint [77.60]. Table 77.1 lists nerve transmission speeds for these signals.

Since neurons are only to be found in the spinal cord and the brain, for hand skin, therefore, we can expect signal transfer delays to the spine of around 30–100 ms. Round-trip muscle activation is, therefore, around 70 ms for signals based on skin data [77.61], or around 25 ms for spindle-based signals (we have verified these delays by measuring hand skin-based reflexes by measuring the corresponding electromyography(EMG) signals, and found a round-trip delay of around 75 ms. Spindle-based feedback for the wrist was measured at around 25 ms.

Of course, when a sensory signal has to be processed in the brain, the delays are correspondingly longer. At any rate: error-correcting feedback control has delays of several tens of milliseconds; feedback control based on such delays cannot lead to any acceptable accuracy with the movement speeds that humans typically display. This means that large portions of our movement, over time frames in the order of 100 ms or more, need to be controlled open loop.

A second important observation is our generalizing capabilities. Consider the case of playing fast and accurate sports, e.g., table tennis. During play, we obtain sensory visual, haptic, and tactile sensory data, the result of which must lead to an accurate movement of the bat in order to score a point. Even a player with little training is able to do this rather accurately: at ball flight times between 200 and 500 ms, the brain does not have much time to plan an accurate whole-body movement for each and every possible sensory state, but we are usually capable of returning the ball. Training helps, but we do not need to exhaustively learn many states in the very high-dimensional sensor space in which our observations move.

Generalization can only be done with reasonably accurate models of the sensor/motor behavior. How-

ever, models of our motor system are difficult to obtain: variations such as including payloads, wearing heavy clothing, muscle fatigue, etc., do not influence our accuracy considerably.

77.3.1 The Flat Hierarchy of Neurocontrol

How is an open-loop movement generated? In this paper we concentrate on voluntary vertebrate motor control; the only reason for any animal to have a brain is to generate movement. Moreover, despite differences in brain structures, there is a large correspondence in movement patterns among the whole animal kingdom, irrespective of the presence of a cortical structure or a cerebellum. What parts of the brain are directly involved in movement?

The major role of the cerebral cortex seems to be unsupervised learning to establish relationships between sensory and action patterns [77.62]. The neocortex is only to be found in mammals; experiments with decorticated cats [77.63] clearly show that the cortex is not necessary to generate movement; rather, it is likely that the motor cortex models and weighs movements, to subsequently make decisions based thereon.

The major role of the basal ganglia seems to be reinforcement learning to filter out unwanted movements [77.62]. They play a dominant role in movement generation or gating (filtering) of generated movement patterns. The effect of Parkinson’s disease (the inability to initiate movement) and Huntington’s disease (the inability to prevent unwanted movement) on the basal ganglia is well known and clearly indicates their function.

The major role of the cerebellum seems to be supervised learning of motor patterns [77.62]. Moreover, decerebellation does not lead to complete movement loss. An individual with cerebellar lesions may be able to move the arm to successfully reach a target and to successfully adjust the hand to the size of an object. However, the action cannot be made swiftly and accurately, and the ability to coordinate the timing of the two subactions is lacking. The behavior will thus exhibit decomposition of movement – first the hand is moved until the thumb touches the object, and only then is the hand shaped appropriately to grasp the object [77.64].

Robot control usually favors a strict hierarchical approach. A typical robot works as follows. At the low-

est level, a very fast ($\approx 100 \mu\text{s}$) current control loop controls the rotation of the dc motor. On top of that, a torque controller (running typically at 1 kHz) controls the torque of all joints, and is in its turn controlled by an impedance or position controller. On top of that, typically, a Cartesian path planner forms the slowest loop. An error in any of these elements will disable the robot.

A look into evolutionary development of neural control thus makes immediately clear that a strict hierarchical approach is not viable in neural control. Although any of the above-mentioned brain regions is important in movement control, and similar structures can be found in any vertebrate, their dysfunction leads to movement degradation but not to movement loss (this is, of course, not true for the spinal cord, which (combines and) transmits the controls to the muscles). Also, the development of the neural system shows that animals were always capable of movement – irrespective of their brain structure. However, the cerebellum is usually rightly focused upon when analyzing vertebrate movement. How do the parts of the brain collaborate towards smooth goal-directed movement?

In placing the function of the cerebellum in the loop, a normal distinction is to consider the cerebellum as representing (a) a forward or direct model which represents the path from motor command to motor output, or (b) an inverse model of motor function, i.e., going from a desired motor outcome to a set of motor commands likely to achieve it. As we have just suggested, the action plan unfolds as if it were feedforward or open loop when the actual parameters of the situation match the stored parameters, while a feedback component is employed to counteract disturbances (current feedback) and to learn from mistakes (learning from feedback). This is obtained by relying on a forward model that predicts the outcome of the action as it unfolds in real time. The accuracy of the forward model can be evaluated by comparing the output generated by the system with the signals derived from sensory feedback (Miall et al. [77.65]). Also, delays must be accounted for to address the different propagation times of the neural pathways carrying the predicted and actual outcome of the action. Note that the forward model in this case is relatively simple, predicting only the motor output in advance; since motor commands are generated internally it is easy to imagine a predictor for these signals (known as an efference copy). The inverse model, on the other hand, is much more complicated since it maps sensory feedback (e.g., vision) back into motor terms.

We suggest a much simpler approach to the vertebrate control system. However, let us first look into the functionality of the lower-level apparatus: muscle, spinal cord, and cerebellum.

77.3.2 On Spinal Cord and Muscle

The key element in movement generation is given by two building blocks: (a) our muscles, and (b) the spinal cord. Muscle behavior is strongly nonlinear; the exerted force decreases nonlinearly with velocity (Fig. 77.3) and varies nonlinearly with length (Fig. 77.4).

Limb movement, however, is caused by a complex of muscles – for instance, the human arm uses a total of 19 muscle groups for planar motion of the elbow and shoulder alone (Nijhof and Kouwenhoven [77.67]) with altogether highly nonlinear dynamics. How can this large number of actuators be controlled without feedback error control?

The concept is simple and was first well described by Bernstein [77.68]: skeletal muscles are always controlled in functional groups, leading to *synergies* of movement. Rather than activating muscles indepen-

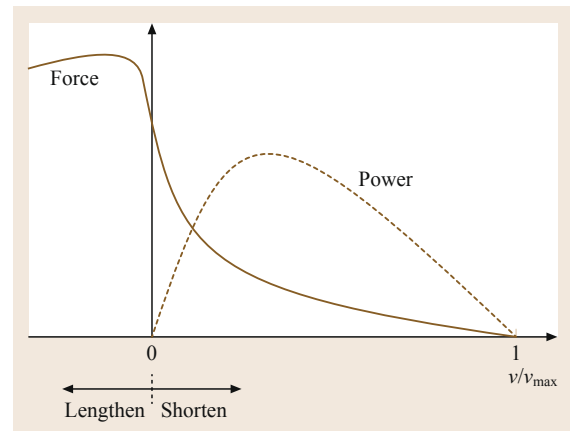


Fig. 77.3 The force/velocity and power/velocity relationship of muscle (after [77.56])

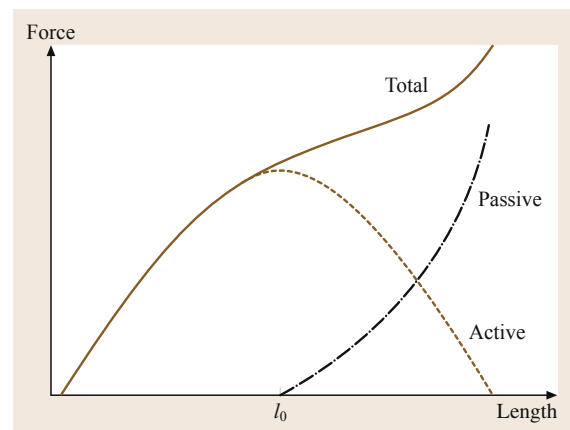


Fig. 77.4 The force/length relationship of muscle (after [77.56])

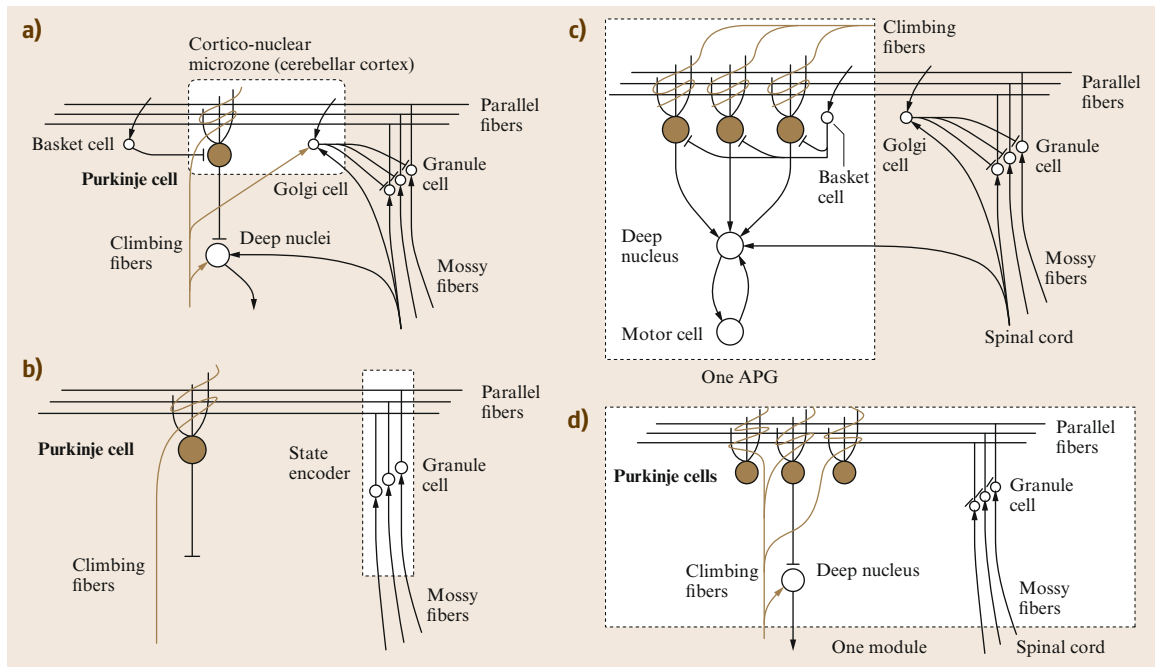


Fig. 77.5 (a) Major cells in the cerebellum. (b) Cells in the Marr–Albus model. The granule cells are state encoders, feeding system state, and sensor data into the PC. PC/PF synapses are adjusted using the Widrow–Hoff rule. The output of the PC are steering signals for the robotic system. (c) The APG model, using the same state encoder as in (b). (d) The MPFIM model. A single module corresponds to a group of Purkinje cells: predictor, controller, and responsibility estimator. The granule cells generate the necessary basis functions of the original information (after [77.66])

dently, a neural signal controls groups of muscles that perform (a part of) an action. Linear dimension reduction methods [77.69] (e.g., principal component analysis, (PCA), independent component analysis (ICA), or non-negative matrix factorization (NMF)) have been used to establish synergies in EMG data, and this can be used [77.70] to linearly combine single-finger movement to whole-hand movement in EMG space. So, we cannot control single muscles (i.e., coherent groups of muscle fibers) but rather control muscle groups, the linear combination of which can be used to span a decent part of our voluntary movement.

There are currently still open questions as to the nature of movement synergies: how much of the synergies are defined by the biomechanical structure of our muscles and tendons; how much of it is laid out in the spinal cord; and which part of it is learned in the higher movement control regions?

77.3.3 Models of Cerebellar Control

The cerebellum can be divided into two parts: the cortex and the deep nuclei. There are two systems of fibers bringing input to the both the cortex and nuclei: the mossy fibers and the climbing fibers. The only output

from the cerebellar nucleus comes from cells called Purkinje cells, and they project only to the cerebellar nuclei, where their effect is inhibitory. This inhibition sculpts the output of the nuclei which (the effect varies from nucleus to nucleus) may act by modulating activity in the spinal cord, the mid-brain, or the cerebral cortex. We now turn to models that make explicit use of the cellular structure of the cerebellar cortex (see Eccles et al. [77.71] and Ito [77.72], and also Fig. 77.5a). The human cerebellum has 7–14 million Purkinje cells (PCs), each receiving about 200 000 synapses. Mossy fibers (MFs) arise from the spinal cord and brainstem. They synapse onto granule cells and deep cerebellar nuclei. Granule cells have axons which each project up to form a T, with the bars of the T forming the parallel fibers (PFs). Each PF synapses on about 200 PCs. The PCs, which are grouped into microzones, inhibit the deep nuclei. PCs with their target cells in cerebellar nuclei are grouped together in microcomplexes [77.72]. Microcomplexes are defined by a variety of criteria to serve as the units of analysis of cerebellar influence on specific types of motor activity. The climbing fibers (CFs) arise from the inferior olive (IO). Each PC receives synapses from only one CF, but a CF makes about 300 excitatory synapses on each PC that it con-

tacts. This powerful input alone is enough to fire the **PC**, though most **PC** firing depends on subtle patterns of **PF** activity. The cerebellar cortex also contains a variety of inhibitory interneurons. The basket cell is activated by **PF** afferents and makes inhibitory synapses onto **PCs**. Golgi cells receive input from **PFs**, **MFs**, and **CFs**, and inhibit granule cells.

The Marr–Albus Model

In the Marr–Albus model (Marr [77.73] and Albus [77.74]) the cerebellum functions as a classifier of sensory and motor patterns received through the **MFs**. Only a small fraction of the parallel fibers (**PF**) are active when a Purkinje cell (**PC**) fires and thus influence the motor neurons. Both Marr and Albus hypothesized that the error signals for improving **PC** firing in response to **PF**, and thus **MF** input were provided by the climbing fibers (**CF**), since only one **CF** affects a given **PC**. However, Marr hypothesized that **CF** activity would strengthen the active **PF/PC** synapses using a Widrow–Hoff learning rule, whereas Albus hypothesized they would weaken them. This is an important example of a case where computational modeling inspired important experimentation. Eventually, Masao Ito was able to demonstrate that Albus was correct – the weakening of active synapses is now known to involve a process called long-term depression [77.72]. However, the rule with weakening of synapses is still known as the Marr–Albus model, and remains the reference model for studies of synaptic plasticity of the cerebellar cortex. However, both Marr and Albus viewed each **PC** as functioning as a perceptron whose job it was to control an elemental movement, contrasting with more plausible models in which **PCs** serve to modulate the involvement of microcomplexes (which include cells of the deep nuclei) in motor pattern generators (e.g., the **APG** model described below).

Since the development of the Marr–Albus model several cerebellar models have been introduced in which cerebellar plasticity plays a key role. Limiting our overview to computational models, we will describe:

1. The **CMAC** (cerebellar model articulation controller).
2. The adjustable pattern generator (**APG**).
3. The Schweighofer–Arbib model.
4. The multiple paired forward-inverse models [77.75, 76].

The Cerebellar Model Articulation Controller

One of the first well-known computational models of the cerebellum is the **CMAC** (Albus [77.77]; Fig. 77.5b). The algorithm was based on Albus' un-

derstanding of the cerebellum, but it was not proposed as a biologically plausible model. The idea has its origins in the BOXES approach, in which for n variables an n -dimensional hypercube stores function values in a lookup table. BOXES suffers from the curse of dimensionality: if each variable can be discretized into D different steps, the hypercube has to store D^n function values in memory. Albus assumed that the mossy fibers provided discretized function values. If the signal on a mossy fiber is in the receptive field of a particular granule cell, it fires onto a parallel fiber. This mapping of inputs onto binary output variables is often considered to be the generalization mechanism in **CMAC**. The learning signals are provided by the climbing fibers.

Albus' **CMAC** can be described in terms of a large set of overlapping, multidimensional receptive fields with finite boundaries. Every input vector falls within the range of some local receptive fields. The response of **CMAC** to a given input is determined by the average of the responses of the receptive fields excited by that input. Similarly, the training for a given input vector affects only the parameters of the excited receptive fields.

The organization of the receptive fields of a typical Albus **CMAC** with a two-dimensional input space can be described as follows. The set of overlapping receptive fields is divided into C subsets, commonly referred to as *layers*. Any input vector excites one receptive field from each layer, for a total of C excited receptive fields for any input. The overlap of the receptive fields produces input generalization, while the offset of the adjacent layers of receptive fields produces input quantization. The ratio of the width of each receptive field (input generalization) to the offset between adjacent layers of receptive fields (input quantization) must be equal to C for all dimensions of the input space. This organization of the receptive fields guarantees that only a fixed number, C , of receptive fields is excited by any input.

If a receptive field is excited, its response equals the magnitude of a single adjustable weight specific to that receptive field. The **CMAC** output is the average of the weights of the excited receptive fields. If nearby points in the input space excite the same receptive fields, they produce the same output value. The output only changes when the input crosses one of the receptive field boundaries. The Albus **CMAC** thus produces piecewise-constant outputs. Learning takes place as described above.

CMAC neural networks have been applied in various control situations Miller [77.78], starting from adaptation of **PID** (proportional–integral–derivative) control parameters for an industrial robot arm and

hand–eye systems up to biped walking (see, for instance, *Sabourin and Bruneau [77.79]*).

The Adjustable Pattern Generator APG

The APG model (*Houk et al. [77.80]*) got its name because the model can generate a burst command with adjustable intensity and duration. The APG is based on the same understanding of the mossy fiber–granule cell–parallel fiber structure as CMAC, using the same state encoder, but has the crucial difference (Fig. 77.2c) that the role of the nuclei is crucial. In the APG model, each nucleus cell is connected to a motor cell in a feedback circuit. Activity in the loop is then modulated by Purkinje cell inhibition, a modeling idea introduced by *Arbib et al. [77.81]*.

The learning algorithm determines which of the PF–PC synapses will be updated in order to improve movement generation performance. This is the traditional credit assignment problem: *which* synapse (the structural credit assignment) must be updated based on a response issued *when* (temporal credit assignment). While the former is solved by the CFs, which are considered binary signals, for the latter eligibility traces on the synapses are introduced, serving as memory for recent activity to determine which synapses are eligible for updates. The motivation for the eligibility signal is this: each firing of a PC cell will take some time to affect the animal’s movement, and a further delay will occur before the CF can signal an error in the movement in which the PC is involved. Thus the error signal should not affect those PF–PC synapses that are currently active, but should instead act upon those synapses that affected the activity whose error is now being registered.

The Schweighofer–Arbib Model

The Schweighofer–Arbib model was introduced in *Schweighofer [77.82]*. It does not use the CMAC state encoder but tries to copy the anatomy of the cerebellum. All the cells, fibers, and axons in Fig. 77.2a are included. Several assumptions are made:

1. There are two types of mossy fibers, one type reflecting the desired state of the controlled plant and another carrying information on the current state. A mossy fiber diverges into approximately 16 branches.
2. Granule cells have an average of four dendrites, each of which receive input from different mossy fibers through a synaptic structure called the glomerulus.
3. Three Golgi cells synapse on a granule cell through the glomerulus and the strength of their influence depends on the simulated geometric distance between the glomerulus and the Golgi cell.

4. The climbing fiber connection on nuclear cells as well as deep nuclei is neglected.

Learning in this model depends on directed error information given by the climbing fibers from the inferior olive (IO). Here, long-term depression is performed when the IO firing rate provides an error signal for an eligible synapse, while compensatory but slower increases in synaptic strength can occur when no error signal is present. Schweighofer applied the model to explain several acknowledged cerebellar system functions:

1. Saccadic eye movements
2. Two-link limb movement control *Schweighofer et al. [77.83, 84]*
3. Prism adaptation (*Arbib et al. [77.85]*).

Furthermore, control of a simulated human arm was demonstrated.

Multiple Paired Forward–Inverse Models (MPFIM)

Building on a long history of cerebellar modeling, *Wolpert and Kawato [77.86]* proposed a functional model of the cerebellum, which uses multiple coupled predictors and controllers that are trained for control, each being responsible for a small state-space region. The MPFIM model is based on the indirect/direct model approach by Kawato, and is also based on the microcomplex theory. We noted earlier that a microzone is a group of PCs, while a microcomplex combines the PCs of a microzone with their target cells in cerebellar nuclei. In MPFIM, a microzone consists of a set of modules controlling the same degree of freedom and is learned by only one particular climbing fiber. The modules in this microzone compete to control this particular synergy. Inside such a module there are three types of PC, which perform the computations of a forward model, an inverse model, or a responsibility predictor, but all receiving the same input. A single internal model i is considered to be a controller that generates a motor command τ_i and a predictor that predicts the current acceleration. Each predictor is a forward model of the controlled system, while each controller contains an inverse model of the system in a region of specialization. The responsibility signal weights the contribution that this model will make to the overall output of the microzone. Indeed, MPFIM further assumes that each microzone contains n internal models of situations occurring in the control task. Model i generates motor command τ_i , and estimates its own responsibility r_i . The feedforward motor command τ_{ff} consists only of the output of the single models adjusted by the sum of responsibility signals: $\tau_{ff} = \sum r_i \tau_i / \sum r_i$.

The **PCs** are considered to be roughly linear. The **MF** inputs carry all necessary information including state information, efference copies of the last motor commands, as well as desired states. Granule cells, and eventually the inhibitory interneurons as well, nonlinearly transform the state information to provide a rich set of basis functions through the **PFs**. A climbing fiber carries a scalar error signal while each Purkinje cell encodes a scalar output – responsibilities, predictions, and controller outputs are all one-dimensional values. **MP-FIM** has been introduced with different learning methods: its first implementations were done using gradient descent methods; subsequently, expectation maximization (**EM**) batch-learning, and hidden Markov chain **EM** learning were applied.

Comparison of the Models

Summing up, we can categorize the cerebellar models **CMAC**, **APG**, Schweighofer–Arbib, and **MPFIM** as follows:

- *State-encoder-driven models*: This kind of model assumes that the granule cells are on-off types of entities that split up the state space. This kind of model is best suited for, e.g., simple function approximation, and suffers strongly from the curse of dimensionality.
- *Cellular-level models*: Obviously, the most realistic simulations would be at the cellular level. Unfortunately, modeling only a few Purkinje cells at realistic conditions is an immense computational challenge, and other relevant neurons are even less well understood. Still, from the biological point of view this kind of model is the most important since it allows obtaining insight into cerebellar function on cellular level. The first steps in this direction were taken by the Schweighofer–Arbib model.
- *Functional models*: From the computer-science point of view, the most interesting models are based on functional understanding of the cells. In this case, we obtain only a basic insight of the functions of the parts and apply it as a crude approximation. This kind of approach is very promising and **MP-FIM**, with its emphasis on the use of responsibility signals to combine models appropriately, provides an interesting example of this approach.

Proprioceptive feedback is used for adaptation of the motor programs as well as for updating the forward model stored in the cerebellum. However, the Schweighofer–Arbib model is based on the view that the cerebellum offers not so much a total forward model of the skeletomuscular system as a forward model of the difference between the crude model of the skeletomus-

cular system available to the motor planning circuits of the cerebral cortex, and the more intricately parameterized forward model of the skeletomuscular system needed to support fast, graceful movements with minimal use of feedback. This hypothesis is reinforced by the fact that cerebellar lesions do not prohibit motion but substantially reduce its quality, since the forward model of the skeletomuscular system is of lesser quality.

77.3.4 Cerebellar Models and Robotics

From the previous discussions, it is clear that a popular view is that the function of the cerebellum within the motor control loop is to represent a forward model of the skeletomuscular system; but how can these models be used in control?

Our assumption is that the cerebellum stores motor primitive relationships, which can be recalled through a certain state (i. e., sensor plus cerebrum-directed goal) input. These motor primitives perform certain coordinated movements (*synergies*) to, e.g., intercept a ball with a tennis racket. A key property of the underlying spine-controlled musculoskeletal system, however, is that *voluntary movement can be easily interpolated* within the control realm of the spinal cord. With this we mean that the combination of two movement primitives that are *nearby* in the relevant sensor domain will lead to a good prediction. *In one possible interpretation, the spinal cord-based control of our muscular system is approximately linear or linearized through internal models* [77.87]. It allows the cerebellum to store or recall movements at any level of granularity, and get good enough results in unlearned areas. There are various papers which, in part, confirm this theory (e.g., *Osu* and *Gomi* show the linear relationship between muscle activation and joint stiffness [77.88] or Höppner et al. between grip force and stiffness [77.89]).

Does this understanding of the human control system help robotics? Biological control algorithms are certainly a result of slow feedback loops and the flexibility of the actuators. One may argue that, as robotic systems move towards their biological counterparts, the control approaches can or must do the same. There are many lines of research investigating the former part; Chaps. 11 and 75. It should be noted that the drive principle that is used to move the joints does not necessarily have a major impact on the outer control loop. Whether McKibben muscles, which are intrinsically flexible but bulky (*van der Smagt* et al. [77.90]), low-dynamics polymer linear actuators, or direct-current (**DC**) motors with spindles and added elastic components are used does not affect the control approach at the cerebellar level, but rather at the motor control level (cf. the spinal

cord level). Of key importance, however, are the resulting dynamic properties of the system, which are, of course, influenced by its actuators. Linearity of the low-level control system, as we find in biology, is a goal to

strive for. Yet technical systems can benefit from advanced modeling approaches, and equally good results can be obtained – yet at the cost of more complex sensing, computation, and less generalizability.

77.4 The Role of Mirror Systems

Area **F5** (frontal area 5) in the premotor cortex of the macaque contains, among others, neurons which fire when the monkey executes a specific manual action, e.g., one neuron might fire when the monkey performs a precision pinch, another when it executes a power grasp. (In discussing neurorobotics, it seems unnecessary to explain in any detail the areas like **F5**, **AIP** (anterior intraparietal sulcus), and **STS** (superior temporal sulcus) described here – they will function as labels for components of functional systems. To fill in the missing details see, e.g., *Rizzolatti et al.* [77.91, 92].)

77.4.1 Mirror Neurons and the Recognition of Hand Actions

A subset of these neurons, the so-called *mirror neurons*, also discharge when the monkey observes meaningful hand movements made by the experimenter, which are similar to those whose execution is associated with the firing of the neuron. In contrast, the *canonical neurons* are those belonging to the complementary, anatomically segregated subset of grasp-related **F5** neurons, which fire when the monkey performs a specific action and also when it sees an object as a possible target of such an action – but do not fire when the monkey sees another monkey or human perform the action. Finally, **F5** contains a large population of motor neurons that are active when the monkey grasps an object (either with the hand or mouth) but do not possess any visual response. **F5** is clearly a motor area although the details of the muscular activation are abstracted out – **F5** neurons can be effector-independent. In contrast, the primary motor cortex (**F1**) formulates the neural instructions for lower motor areas and motor neurons.

Moreover, macaque mirror neurons encode transitive actions and do not fire when the monkey sees the hand movement unless it can also see the object or, more subtly, if the object is not visible but is appropriately *located* in working memory because it has recently been placed on a surface and has then been obscured by a screen behind which the experimenter is seen to be reaching (*Umiltà et al.* [77.93]). All mirror neurons show visual generalization. They fire when the instrument of the observed action (usually a hand) is large or small, far from or close to the monkey.

They may also fire even when the action instrument has shapes as different as those of a human or monkey hand. Some neurons respond even when the object is grasped by the mouth. When naive monkeys first see small objects grasped with a pair of pliers, mirror neurons do not respond, but after extensive training some precision pinch mirror neurons do show activity, also with this new grasp type [77.94].

Mirror neurons for grasping have also been found in parietal areas of the macaque brain and, recently, it was shown that parietal mirror neurons are sensitive to the context of the observed action being predictive of the outcome as a function of contextual cues – e.g., some grasp-related parietal mirror neurons may fire for a grasp that precedes eating the grasped object, while others fire for a grasp that precedes placing the object in a container (*Fogassi et al.* [77.95]). In practice, the parieto-frontal circuitry seems to encode action execution and simultaneously action recognition by taking into account a large set of potential candidate actions, which are selected on the basis of a range of cues such as vision of the relation of the effector to the object and certain sounds (when relevant for the task). Further, feedback connections (frontal to parietal) are thought to be part of a stimulus selection process that refines the sensory processing by *attending* to stimuli relevant for the ongoing action (*Rizzolatti et al.* [77.52] and recall the discussion in Sect. 77.2.4). Recognition is then supported by the activation of the same circuitry in the absence of overt movement.

We clarify these ideas by briefly presenting the **FARS** model of the canonical **F5** neurons and the **MNS** model of the **F5** mirror neurons. In each case, the **F5** neurons function effectively only because of the interaction of **F5** with a wide range of other regions. We have stressed (Sect. 77.2.3) the distinction between recognition of the category of an object and recognition of its *affordances*. The parietal area **AIP** processes visual information to extract *affordances*, in this case properties of the object relevant to grasping it (*Taira et al.* [77.96]). **AIP** and **F5** are reciprocally connected, with **AIP** being more visual and **F5** more motoric.

The Fagg–Arbib–Rizzolatti–Sakata (**FARS**) model (*Fagg and Arbib* [77.97] and Fig. 77.6) embeds **F5** canonical neurons in a larger system. The dorsal stream

(which passes through **AIP**) can only analyze the object as a set of possible affordances, whereas the ventral stream (via the inferotemporal cortex, **IT**) is able to recognize what the object is. The latter information is passed to the prefrontal cortex (**PFC**) which can then, on the basis of the current goals of the organism, bias the choice of affordances appropriate to the task at hand. Neuroanatomical data (as analyzed by *Rizzolatti and Luppino* [77.98]) suggest that **PFC** and **IT** may modulate action selection at the level of the parietal cortex. Figure 77.6 gives a partial view of the **FARS** model updated to show this modified pathway. The affordance selected by **AIP** activates **F5** neurons to command the appropriate grip once they receive a *go* signal from another region, **F6**, of the prefrontal cortex. **F5** also accepts signals from other **PFC** areas to respond to working memory and instruction stimuli in choosing among the available affordances. Note that this same pathway could be implicated in tool use, bringing in semantic knowledge as well as perceptual attributes to guide the dorsal system (*Johnson-Frey* [77.99]).

With this, we turn to the *mirror* system. Since grasping a complex object requires careful attention to motion of, e.g., fingertips relative to the object, we hold that the primary evolutionary impetus for the mirror system was to facilitate feedback control of dexterous movement. We now show how *parameters relevant to such feedback* could be crucial in enabling the monkey to associate the visual appearance of what it is doing with the task at hand. The key side-effect will be that this feedback-serving self-recognition is so structured as to also support recognition of the action when performed by others – and it is this *recognition of the*

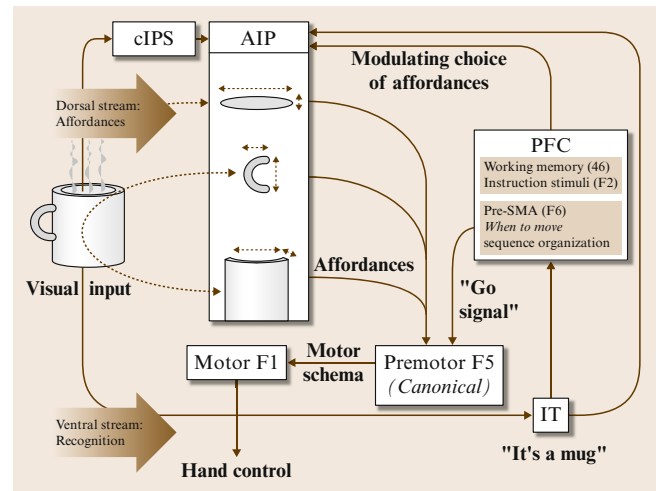


Fig. 77.6 The original **FARS** diagram (after *Fagg and Arbib* [77.42]) is here modified to show **PFC** acting on **AIP** rather than **F5**. The idea is that the prefrontal cortex uses the **IT** identification of the object, in concert with task analysis and working memory, to help the **AIP** select the appropriate affordance from its *menu*

actions of others that has created the greatest interest in mirror neurons and systems.

The **MNS** model of *Oztop and Arbib* [77.101] provides some insight into the anatomy while focusing on the learning capacities of mirror neurons. Here, the task is to determine whether the shape of the hand and its trajectory are *on track* to grasp an observed affordance of an object using a known action. The model is organized around the idea that the **AIP** → **F5_{canonical}** pathway emphasized in the **FARS** model (Fig. 77.6) is

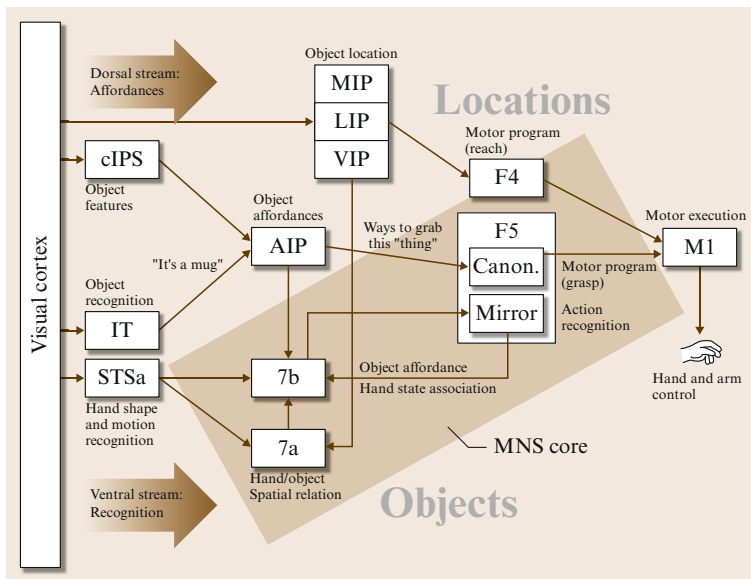


Fig. 77.7 The mirror neuron system (**MNS**) model (after *Oztop and Arbib* [77.100]). Note that this basic mirror system for grasping crucially links the visual process of the **STS** to the parietal regions (**b**) and premotor regions (**F5**), which have been shown to contain mirror neurons for manual actions

complemented by another pathway $7b \rightarrow F5_{\text{mirror}}$. As shown in Fig. 77.7 (middle diagonal), object features are processed by AIP to extract grasp affordances; these are sent on to the canonical neurons of F5 that choose a particular grasp. Recognizing the location of the object (top diagonal) provides parameters to the motor programming area F4 which computes the reach. The information about the reach and the grasp is taken by the motor cortex M1 (= F1) to control the hand and the arm. The rest of the figure provides components that can learn and apply key criteria for activating a mirror neuron, recognizing that the preshape of the observed hand corresponds to the grasp that the mirror neuron encodes and is appropriate to the object, and that the hand is moving on an appropriate trajectory. Making crucial use of input from the superior temporal sulcus (Perrett et al. [77.102] and Carey et al. [77.103]), schemas at the bottom left recognize the shape of the observed hand and how that hand is moving. Other schemas implement hand–object spatial relation analysis and check how object affordances relate to hand state. Together with F5 canonical neurons, this last schema (in parietal area 7b) provides the input to the F5 mirror neurons.

In the MNS model, the *hand state* was defined as a vector whose components represented the movement of the wrist relative to the location of the object and of the hand shape relative to the affordances of the object. Oztop and Arbib showed that an artificial neural network corresponding to PF and $F5_{\text{mirror}}$ could be trained to recognize the grasp type from the *hand state trajectory*, with correct classification often being achieved well before the hand reached the object, using activity in the F5 canonical neurons that commands a grasp as training signal for recognizing it visually; this basically shows that there is a causal relationship. Crucially, this training prepares the F5 mirror neurons to respond to hand–object relational trajectories even when the hand is of the *other* rather than the *self* because the hand state is based on the view of movement of a hand relative to the object, and thus only *indirectly* on the retinal input of seeing the hand and object, which can differ greatly between observation of self and other. Bonaiuto et al. [77.104] have developed MNS2, a new version of the MNS model to address data on audiovisual mirror neurons that respond to the sight and sound of actions with characteristic sounds such as paper tearing and nut cracking Kohler et al. [77.93], and on the response of mirror neurons when the target object was recently visible but is currently hidden Umiltà et al. [77.93]. Such learning models, and the data they address, make it clear that:

mirror neurons are not restricted to recognition of an innate set of actions but can be recruited to rec-

ognize and encode an expanding repertoire of novel actions.

The discussion of this section avoided any reference to imitation (Sect. 77.4.3). On the other hand, even without considering imitation, mirror neurons provide a new perspective for tackling the problem of robotic perception by incorporating action (and motor information) into a plausible recognition process. The role of the fronto-parietal system in relating affordances, plans, and actions shows the crucial role of motor information and embodiment. We argue that this holds lessons for neurorobotics: the richness of the *motor* system should strongly influence what the robot can learn, proceeding autonomously via a process of exploration of the environment rather than overly relying on the intermediary of logic-like formalisms. When recognition exploits the ability to act, then the breadth of the action space becomes crucially related to the precision, quality, and robustness of the robot's perception.

77.4.2 Computational Models

Roboticians have been fascinated by the discovery of mirror neurons and the purported link to imitation that exists in the human nervous system, for they can help to teach robots new tasks with relative ease. The literature on the topic extends from models of the monkey's (nonimitative) action recognition system (Oztop and Arbib [77.101]) to models of the putative role of the mirror system in imitation (Demiris and Johnson [77.105] and Arbib et al. [77.106]), and in real and virtual robots (Schaal et al. [77.107]). Oztop et al. [77.108] propose a taxonomy of the models of the mirror system for recognition and imitation, and it is interesting to note how different the computational approaches that have now been framed as mirror system models are, including recurrent neural networks with parametric bias (Tani et al. [77.109]), behavior-based modular networks (Demiris and Johnson [77.105]), associative memory-based methods (Kuniyoshi et al. [77.110]), and the use of multiple direct-inverse models as in the MOSAIC architecture (Wolpert et al. [77.111]; cf. the multiple paired forward-inverse models of Sect. 77.3.2).

Following [77.112], we can cast much that is known about the mirror system into a controller-predictor model [77.65, 113] and analyze the resulting model as a Bayesian classifier. As shown by the FARS model, the decision to initiate a particular grasping action is attained by the convergence in area F5 of several factors, including contextual and object-related information; similarly many factors affect the recognition of an action. All this depends on learning both direct (from decision to executed action) and inverse models

(from observation of an action to activation of a motor command that could yield it). Similar procedures are well known in the computational motor control literature [77.114, 115]. Learning of the affordances of objects with respect to grasping can also be achieved autonomously by learning from the consequences of applying many different actions to different parts of different objects.

However, how is the decision made to classify an observed behavior as an instance of one action or another? Many comparisons could be performed in parallel with the models for one action to become predominantly activated. There are plausible implementations of this mechanism using a gating network [77.105, 116]. A gating network learns to partition an input space into regions; for each region a different model can be applied or a set of models can be combined through an appropriate weight function. The design of the gating network can encourage collaboration between models (e.g., linear combination of models) or competition (choosing only one model rather than a combination). Reference [77.117] offers a similar approach to the estimation of the mental states of the observed actor, using some additional circuitry involving the frontal cortex.

On the other hand, if we take the Bayesian view of the predictor-controller formulation, then affordances are simply the priors in the action recognition process where the evidence is conveyed by the visual information of the hand, providing the data for finding the posterior probabilities as mirror neuron-like responses which automatically activate for the most probable observed action. Recall that the presence of a goal (at least in working memory) is needed to elicit mirror neuron responses in the macaque. We believe it is also particularly important during the ontogenesis of the human mirror system. For example, [77.118] has shown that even at 9 months of age, infants recognized an action as being novel if it was directed toward a novel object rather than just having a different kinematics – showing that the goal is more fundamental than the enacted trajectory. Similarly, if one sees someone drinking from a coffee mug then one can hypothesize that a particular action (that one already knows in motor terms) is used to obtain that particular effect. The association between the canonical response (object-action) and the mirror one (including vision) is made when the observed consequences (or goal) are recognized as similar in the two cases. Similarity can be evaluated following criteria ranging from kinematic to social consequences.

In a similar experiment *Lopes et al.* [77.119] compared action recognition performance (a) when using the output of an inverse visuo-motor model and thus

employing motor features to aid classification during the training phase, and (b) when only visual data were available for recognition. Overall, their interpretation of the results is that by mapping in motor space through inverse model mapping, they allow the classifier to choose features that are much better suited for performing optimally with respect to the task of recognizing actions, which in turn facilitates generalization. The same is not true when recognition is performed purely in visual space using generic visual features, since a given action is viewed from different viewpoints. One may compare this to the viewpoint-invariant hand state adopted in the *MNS* model – which has the weakness of being built in rather than emerging from training.

Along the same line, the work of *Gijsberts et al.* [77.120] included motorically-derived affordance information, which was recorded using a data-glove-based system and a set of cameras. In this case though, motor information was not much for action recognition but rather used to *simulate* the response of *F5*'s canonical neurons by generating discrete grasping types from the time-varying set of postures recorded with the data glove. After training the original motor information is removed and only reconstructed using an inverse model. Furthermore, this motoric information was combined with a simulation of the brain ventral pathway which extracts pictorial features from images (e.g., *SIFT* (scale-invariant feature transform), *H-Max*). The dorsal and ventral features were combined through a special kernel function in a simple least squares classifier, showing a significant improvement at recognizing objects in comparison to a purely visual classification. A machine learning framework to address the question of learning from multimodal signals (some of which can even be intermittent) is presented in [77.121].

We can speculate that this computational advantage (better recognition rates) makes the presence of mixed sensory and motor information compelling in the brain (i.e., the fronto-parietal system); this may not necessarily lead to mirror neurons although it seems plausible that any clear advantage of using information at best is eventually selected during evolution. These experiments, using robots, simulations, and computational arguments can thus explain the whys of certain brain structures and mechanisms.

77.4.3 Mirror Neurons and Imitation

Fitzpatrick and Metta [77.122] also addressed the question of what is further required for interpreting observed actions. Whereas in observing its own actions, the robot identifies them from the effects on the objects, later it could backtrack and derive the type of action needed to replicate a certain observed effect on a given object.

Therefore, imitation can be framed into the identification of a common goal between the observed action and various possible actions in the *motor repertoire* of the robot. In [77.122] the robot used the same visual processing algorithms both in observing its own hand and the hand of a person (although they were different in appearance). One might argue that observation alone can be used for learning, never relying on active exploration of objects and actions. This is possibly true to the extent that passive vision is reliable and action is not required. The advantage of the active approach, at least for the robot, is that it allows controlling the amount of information impinging on the visual sensors by, for instance, controlling the speed and type of action. This strategy might be especially useful given the limitations of artificial perceptual systems. Thus, observations can be converted into interpreted actions. The action whose effects are closest to the observed consequences on the object (which we might translate into the goal of the action) is selected as the most plausible interpretation given the observation. Most importantly, the interpretation reduces to the interpretation of the *simple* kinematics of the goal and consequences of the action rather than to understanding the *complex* kinematics of the human manipulator. The robot understands only to the extent it has learned to act. One might note that a more refined model should probably include visual cues from the appearance of the manipulator into the interpretation process. Indeed, the *hand state* that was central to the *Oztop-Arbib* model was based on an object-centered view of the hand's trajectory in a coordinate frame based on the object's affordances. The last question to address is whether a robot can imitate the *goal* of the action. The step is indeed small, since most of the complexity is actually in interpreting observations. Imitation can be generated by replicating the latest observed human movement with respect to the object utilizing one of the many approximation methods for motion generation such as, e.g., a mixture of Gaussians [77.123], dynamic motion primitives [77.124], or reinforcement learning [77.125]. More generally, following the work of *Schaal* et al. [77.107] and *Oztop* et al. [77.108] we can propose a set of schemas required to produce imitation:

- Determining what to imitate, inferring the goal of the demonstrator
- Establishing a metric for imitation (correspondence; see *Nehaniv* [77.126])
- Map between dissimilar bodies (mapping).
- Imitating behavior formation.

These are also discussed in greater detail by *Nehaniv* and *Dautenhahn* [77.127]. In practice, computa-

tional and robotic implementations have tackled these problems with different approaches and emphasizing different parts or specific subproblems of the whole, for example, in the work of *Demiris* and *Hayes* [77.128], the rehearsal of the various actions (akin to the aforementioned theory of motor perception) was used to generate hypotheses to be compared with the actual sensory input. It is then remarkable how more recently a modified approach of this paradigm has been used in comparison with real human transcranial magnetic stimulation (TMS) data.

Ito et al. [77.129] (not Masao Ito of cerebellar fame) took a dynamical systems approach using a recurrent neural network with parametric bias (RNNPB) to teach a humanoid robot to manipulate certain objects. In this approach the parametric bias (PB) encodes (tags) certain sensorimotor trajectories. Once learning is complete, the neural network can be used either to recall a given trajectory by setting the PB externally or provide input for the sensory data only and observe the PB vector that would represent in that case the recognition of the situation on the basis of the sensory input only (no motor information available). It is relatively easy to interpret these two situations as the motor generation and the observation in a mirror neurons model.

The problem of building useful mappings between dissimilar bodies (consider a human imitating a bird's flapping wings) was tackled by *Nehaniv* and *Dautenhahn* [77.127] where an algebraic framework for imitation is described and the correspondence problem formally addressed. Any system implementing imitation should clearly provide a mapping between either dissimilar bodies or even in the case of similar bodies when either the kinematics or dynamics is different depending on the context of the imitative action.

Sausser and *Billard* [77.130] modeled the *ideomotor principle*, according to which observing the behavior of others influences our own performances. The ideomotor principle points directly to one of the core issues of the mirror system, that is, the fact that watching somebody else's actions changes something in the activation of the observer, thus facilitating certain neural pathways. The work in question also gives a model implemented in terms of neural fields (see *Sausser* and *Billard* [77.130] for details) and tries to explain the imitative cortical pathways and the behavior formation.

77.4.4 Mirror System and Speech

Already in the 1960s *Lieberman* et al. [77.131] started to discuss the possible links between production and perception in speech: in other words the contribution of articulation into the perception of utterances. Later he commented [77.132]:

A result in all cases is that there is not, first, a cognitive representation of the proximal pattern that is modality-general, followed by a translation to a particular distal property; rather, perception of the distal property is immediate, which is to say that the module has done all the hard work.

Liberman argued that there is no such a thing as a modality-aspecific representation which then becomes speech as an effect of a translation to a specific set of articulators (the vocal apparatus in this case), rather, he claimed that perception of speech is immediate and effected by the same speech module (the same that generates speech); speech remains a motor fact. Lately, theories of the motor involvement in speech perception have gained credit because of the discovery of the mirror neurons. It has been postulated that the mirror system in humans *controls* jointly speech production and perception, whereby the actions in speech are the articulation of appropriate segments of the utterances [77.133].

We recall this line of reasoning in the following [77.133], that is:

- Mirror neurons (or a mirror system) exist in humans [77.134].
- The human mirror system is identified in Broca's area, a cytoarchitectonical homolog of area F5 in the macaque's brain.
- Speech articulation is coded/controlled in/by the areas of the human mirror system (Broca's) [77.135].
- The recognition of the intention of the speaker by the listener owing to a mirror mechanism leads to the first seed of true communication (via, e.g., orofacial gestures) [77.133].
- The combinatorial properties of F5/Broca and the precise control of the effectors are needed to generate speech (the evolutionarily older animal calls are too stereotyped to grant this flexibility that eventually leads to speech proper) [77.136].

To establish that this is the case, however, more empirical evidence is required. Recently, two experiments improved the plausibility of the mirror neurons theory of speech perception. In a first TMS experiment, Fadiga and colleagues [77.137] established that MEPs (motor evoked potentials) in the tongue muscles directly correlate with high specificity to the perception of particular sounds (these were *rr* and *ff* in Italian). The listener was delivered TMS (single pulse) and the observed MEPs correlated in amplitude with the different use of the tongue muscles for the pronunciation of either the *rr* or *ff* sounds (*rr* in Italian requires a strong mobilization of the tongue). Albeit convincing, this experiment leaves

open the question of specificity, since it can still be the case of a diffuse/generic activation of Broca's area.

A second experiment also by Fadiga et al. [77.137] was designed to set the issue. In this case, the TMS was delivered to the primary motor cortex with the aim of establishing a specific motor involvement into the perception of different sounds/phones. Two areas were individuated in the primary motor cortex as responsible to the lip and tongue movement, respectively (e.g., *p/b* sounds versus *t/d*). The data show a double dissociation pattern, that is, when the lip motor area is stimulated there is a decrease of the reaction times (RTs) of the subject in perceiving the *p/b* (labial sounds) and vice-versa an increase for the perception of the *t/d* (dental sounds). The opposite happens when the tongue motor area is stimulated. This experiment clearly relates a very specific (small) region of the primary motor cortex with the perception of certain specific (and related) sounds.

Clearly, this is only part of the story; to complicate matters, for example, the semantic content of words related to actions (e.g., kick, pick, lick) activate both motor and pre-motor brain areas somatotopically. Object features, odors, etc., instead have been shown to generate responses in the corresponding cortices. For a review of these and other results, see [77.136].

Theories and models such as the perception for action control theory (PACT) [77.138] take a more moderate interpretation by including both a motor component and *perceptual shaping*, that is, the filtering of certain linguistic combinations because of purely perceptual characteristics (e.g., separation of vowel formants). In PACT, it is hypothesized that the motor system is activated more in *adverse conditions*, while it is perhaps under-threshold for normal speech understanding in good signal-to-noise conditions.

Indeed, we can recognize speech in a foreign accent, and recognizing what is being said can then be decoupled from being able to articulate how it is being said – but both possibilities are available. This has led to a new view of the integration of mirror systems with other systems [77.139] which downplays the motor theory of speech perception while preserving many other features of the mirror system hypothesis of Rizzolatti and Arbib [77.133].

Armed with these results Castellini and colleagues [77.140] conducted a computational experiment that mimic some of the TMS results of D'Ausilio et al. [77.141]. All processing employed a database of synchronized recordings of Italian speakers with acoustic, articulograph, camera, ultrasound, and electroglottograph data [77.142]. For the experiments, only the articulograph and electroglottograph signals were used together with speech sound. These identify the position of the tongue and teeth versus the lips in

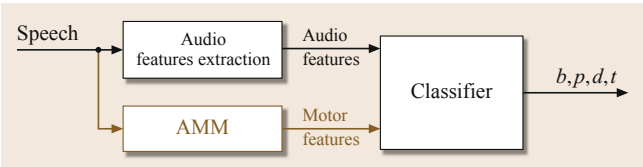


Fig. 77.8 Conceptual schema of the classifiers used in the experiments

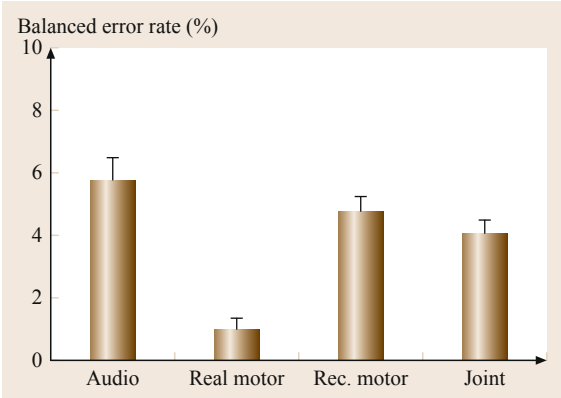


Fig. 77.9 Baseline experiment comparing the performance of acoustic versus motor data (or jointly acoustic plus motor data) in classifying b/p versus d/t

real time (200 Hz) in addition to the activation of the vocal folds (voicing signal). The conceptual schema of all experiments and learning follows some previous work as by Metta et al. [77.112], and which as is shown in Fig. 77.8. In particular, acoustic data are mapped into motoric features and these are used for classifying phones. Similarly to the PACT model, it was found useful to incorporate also a purely acoustic classifier. Acoustic features were the standard Mel cepstral coefficients with similar parameters and frequency

bands of conventional automatic speech recognition (ASR).

The mapping from acoustic to motor data was performed using either an artificial neural network or support vector machine for regression with indistinguishable results. The classifier was always a support vector machine with Gaussian kernel and parameters optimized through grid search.

In order to compare it with the TMS experiments, phones were divided into two classes, the b/p and t/d , respectively, as representing the bi-labial and dental (movement of the tongue toward the teeth) phones. Fivefold cross-validation was employed on all results by either random splits of the data or by selecting data from various participants (e.g., training on 1–5 participants, testing on 1–5 participants). Gaussian white noise was added to the stimuli (at increasing levels from 0 to 150%) to replicate the conditions of the TMS.

Figure 77.9 shows these results. The baseline experiment shows an improved performance where either the real motoric or jointly motoric and acoustic features are used. The comparison of *audio* versus *joint* features is statistically significant ($p < 0.01$) and verifies the claim as no new information is added to the system when the reconstructed motor features are employed. Motor features are *reconstructed* by the audio-motor map (AMM) of Fig. 77.8 and replicates previous results obtained in the classification of hand gestures [77.119] or handwriting characters [77.143].

A second experiment from the same work of Castellini and colleagues [77.140] shows the behavior of the same system in various conditions of increased difficulty ranging from running classification on speakers not included in the training sets to co-articulation. Figure 77.10 shows a number of variants where N vs M indicates N speakers for training versus M speakers for testing given the size of the database (6 speakers). Ex-

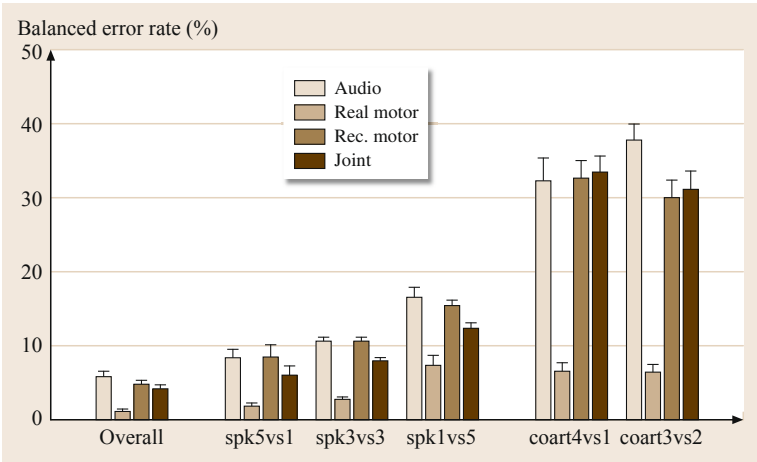


Fig. 77.10 Comparison across various conditions. In all cases apart from coart4vs1 the use of motor features improve classification with statistical significance ($p < 0.01$)

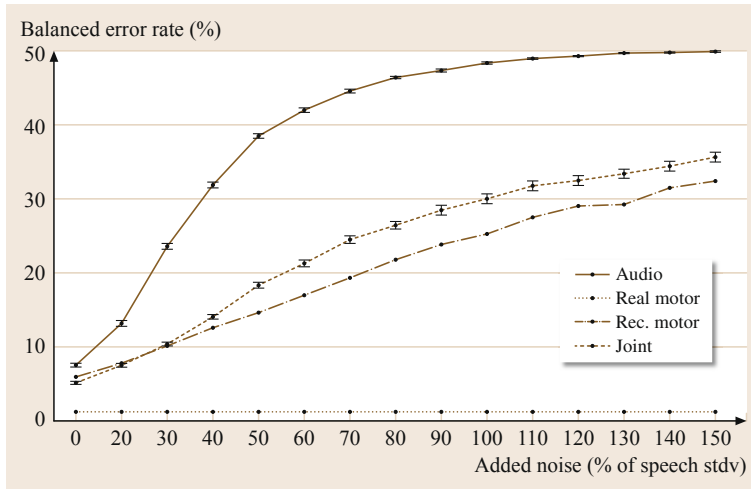


Fig. 77.11 Comparison of acoustic versus motor features under increasing level of added Gaussian white noise for the same classifier of the previous experiments

periments with co-articulation were conducted also on five speakers, albeit the number of identifiable examples in the database was smaller.

In a final experiment, the classifier was tested on acoustic data corrupted by Gaussian white noise. Results show a consistent improvement with the motor information gain increasing with the increase of the noise level (up to 150% of the speech standard deviation): Fig. 77.11.

More recently a full phone classifier was built using similar principles [77.144] together with a combination of deep belief networks (DBNs) and more standard hidden Markov models (HMMs). The results show improvement with respect to the state of the art, continuing the long tradition of neurorobotics and bringing models very close to concrete applications on robots that bear resemblance to the exquisite human performance in speech recognition in noisy environments.

77.5 Conclusion and Further Reading

As the foregoing makes clear, robotics has much to learn from neuroscience and much to teach neuroscience. Neurorobotics can learn from the ways in which the brains and bodies of different creatures adapt to diverse ecological niches – as computational neuroethology helps us understand how the brain of a creature has evolved to serve *action-oriented perception*, and the attendant processes of learning, memory, planning, and social interaction.

We have sampled the *design* of just a few sub-systems (both functional and structural) in just a few animals – optic flow in the bee, approach, escape, and barrier avoidance in frogs and toads, and navigation in the rat, as well as the control of eye movements in visual attention, the role of the mammalian cerebellum in handling the nonlinearities and time delays of flexible motor systems, and the mirror systems of primates in action recognition and of humans in imitation. There are many more creatures with lessons to offer the roboticist than we can sample here.

Moreover, if we just confine attention to the brains of humans, this chapter has mentioned at least 7a,

7b, AIP, lateral, medial and ventral intraparietal sulcus (LIP, MIP and VIP), area 46, basal ganglia, caudoputamen, cerebellum, F2, F4, F5, hippocampus, hypothalamus, inferotemporal cortex, motor cortex, nucleus accumbens, parietal cortex, prefrontal cortex, premotor cortex, pre-SMA (F6), spinal cord, STS, and – and it is clear that there are many more details to be understood for each region, and many more regions whose interactions hold lessons for roboticists. We say this not to depress the reader, but rather to encourage further exploration of the literature of computational neuroscience and to note that the exchange with neurorobotics proceeds both ways: neuroscience can inspire novel robotic designs; conversely, robots can be used to test whether brain models still work when they make the transition from disembodied computer simulation to meeting the challenge of guiding the interactions of a physically embodied system with the complexities of its environment.

Nonetheless, a thorough study of the spinal cord and its effect on muscle behavior is where a roboticist, who is interested in replicating some of the functionality of vertebrate movement, may want to start looking.

77.5.1 Further Reading

- *Arbib* (2006) [77.145]: This volume provides 16 articles on the mirror system, written by diverse experts. Of particular relevance to this chapter are articles on dynamical systems: brain, body and imitation; attention and the minimal subscene; the development of grasping and the mirror system; and development of goal-directed imitation, object manipulation, and language in humans and robots.
- *Bell* (1996) [77.146]: This somewhat older BBS special issue provides what was, back then, a rather definitive number of articles on the cerebellum, including an overview of models in a paper by *Houk* et al.
- *van der Smagt* and *Bullock* (2002) [77.147]: This special issue is focused on the application of cere-

bellar and other models to robotics tasks, and lists some successful and – between the lines – more unsuccessful applications thereof.

- *Gallese* et al. (1996) [77.148]: This paper provides a detailed account of the neurophysiological evidence for mirror neurons. It is good reading to get the real data unbiased from further interpretation on the role of mirror neurons and it is complete and accurate. Although it is a technical paper it is easy to read also for a general audience.
- *Fadiga* et al. 2002 [77.149]: This work extends the mirror system concept with an interesting perspective on its role into language. This paper is interesting reading by providing evidence in humans (the other references above are about monkey experiments). In this case, it has been shown that speech listening facilitates the activation of tongue muscles which match the specific phoneme being listened to.

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78. Perceptual Robotics

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Robots that share their environment with humans need to be able to recognize and manipulate objects and users, perform complex navigation tasks, and interpret and react to human emotional and communicative gestures. In all of these perceptual capabilities, the human brain, however, is still far ahead of robotic systems. Hence, taking clues from the way the human brain solves such complex perceptual tasks will help to design better robots. Similarly, once a robot interacts with humans, its behaviors and reactions will be judged by humans – movements of the robot, for example, should be fluid and graceful, and it should not evoke an *eerie* feeling when interacting with a user. In this chapter, we present Perceptual Robotics as the field of robotics that takes inspiration from perception research and neuroscience to, first, build better perceptual capabilities into robotic systems and, second, to validate the perceptual impact of robotic systems on the user.

78.1 Perceptual Mechanisms of Object Representations 2097

The technical realization of perceptual functions is a central problem for many applications in robotics. Robots require perception to navigate in space and to localize and recognize goal objects, e.g., for manipulation (Chaps. 7, 8, 32, 33, 36–38, 47, 67). Social interactive robots must be able to interpret gestures, actions, and even emotions (Chap. 69, 71, 72) in order to interact naturally with their users. One important approach for the programming of complex perceptual and behavioral functions, for example, needed for humanoid robots is imitation learning (Chaps. 75, 77). Imitation learning requires the robot to *perceive* complex actions

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that are executed by the user and to subsequently map them into an efficient representation that is suitable for the synthesis of the corresponding motor behavior on the available platform. This chapter focuses on important principles of the representation of complex shapes and movements, which can be derived from biological perception systems, and more specifically the basic functionality of the primate visual cortex. Such principles have interesting implications for the design of technical systems in robotics and computer vision for the recognition of objects, shapes and faces, and for the recognition and synthesis of complex movements and

actions. The limited space of the chapter forced us to focus mainly on visual perception and related technical applications. In the context of robotics many other aspects of perception are important, for example haptic perception (Chap. 41), auditory perception, sensory cue fusion (Chap. 35), and the interaction between the visual recognition of objects and actions and motor programs, e.g., during grasping (treated in Chap. 38).

In the following, we will first formulate several biological principles that are relevant for form and motion representations, specifically in the visual system. We will then, on the one hand, describe technical systems that implement these principles using neural mechanisms that are inspired by the basic architecture of the brain. On the other hand, we will discuss also implementations that are inspired by biological principles on a more abstract level, and which exploit instead of neural networks more efficient technical algorithms for the realization of biologically relevant functions. Many of these systems are derived in the field of computer vision and are based on the advantages and limitations of modern digital computers in order to more efficiently realize biological principles of information processing.

Our approach to establish relationships between biological perception and robotics systems at different levels reflects *David Marr's* classical distinction of multiple levels of description, originally developed for the analysis of vision systems [78.1]: Robotics systems can be inspired by biological system at the level of implementation, i. e., one can try to build robots containing neural mechanisms that imitate the function of neurons in central nervous systems of biological organisms. This type of analogy between technical and biological systems coincides with the definition of *Neurorobotics* given in Chap. 77. A transfer of principles from biological perception systems to robots might also be accomplished at the more abstract levels of computational problems and algorithms. The computational level is defined by the abstract theoretical formulation of computational problems that have to be solved by perception systems. Examples are the identification or classification of goal object, or the recognition of human gestures. Marr's level of algorithms specifies the computational methods for the solution of such problems, independent of the underlying specific hardware or architecture. For example, an object might be represented by modeling its full 3-D structure, e.g., using a parametric 3-D shape model, or it might be represented in terms of two-dimensional example views. Example views, however, might be represented using neural networks, establishing an analogy with the human brain at the level of implementation, or using more efficient computational methods, e.g., as support vectors of a classifier that has been trained with appropriate

images of the object and distractor patterns. In both the cases, the robot system realizes mechanisms that are derived from perception in biological systems.

Marr's distinction of levels is only one way to introduce description levels for complex systems. Other approaches, particularly relevant for robotics, are, for example the subsumption architecture and behavior-based approaches (Chap. 13) that decompose robotics system into a system of simpler behavioral modules. Another examples are dynamical systems approaches to robotics [78.2–4] that are based on the biologically motivated idea that behaviors can be mapped onto stable states of (nonlinear) dynamical systems or recurrent neural networks. Individual behaviors result by self-organization over the whole system as collectively stable modes, which can be described and analyzed by the introduction of appropriate collective variables. Interestingly, such robotics-inspired approaches have been quite successful in modeling human navigation behavior [78.5].

In the following, we will apply the term *Perceptual Robotics* to signify the design of robots based on principles that are derived from human perception on all three levels in the sense of Marr. This includes a realization in terms of specific neural circuits as well as the transfer of more abstract biologically inspired strategies for the solution of relevant computational problems. A direct interaction between robotics and perception research can be very fruitful for both disciplines. On the one hand, our current knowledge about the human perception and the underlying computational principles might help us to build more efficient robotics architectures that inherit properties from biological perception, e.g., very efficient and robust processing or complex dynamic flexibility. Such architectures will be a necessary pre-requisite for the creation of truly intelligent, cognitive robots (Chaps. 13, 71, 74, 75). On the other hand, perception science often uses robots as testbed for gaining a deeper understanding of computational processes, in particular, for testing the computational power of specific computational solutions under *real-world conditions*. How can a child, for example, learn how to handle new objects, and what allows us to learn the visual categorization of thousands of objects from just a few examples? *Perceptual robot platforms*, equipped with a variety of sensory inputs and operating in different types of artificially structured or real-world environments provide very helpful tools for the study of such questions.

Finally, perceptual robotics not only means to take inspiration from perception to build more efficient robots, but it also encapsulates the perceptual validation of robotic systems. As robots move into the human environment and are increasingly also interacting with

humans, it becomes important to evaluate and validate their effectiveness and efficacy with respect to human standards. Here, we do not refer to their social acceptance, but rather to the way that robots are judged by humans in terms of their appearance, movements, and interactive capabilities. If a robot displays jerky movements, for example, it may still successfully grasp and manipulate an object, but it would be immediately noticeable to a human observer and potentially disturbing to interact with. This *eeriness* or *weirdness* was already anticipated in the early 1970s in a famous paper about the *uncanny valley* by a Japanese roboticist [78.6]. Mori anticipated that as robots become more human-like, humans' familiarity with the robot would increase until at some point (when the robot looks or acts almost human-like), they would suddenly feel highly unfamiliar toward the robot. As the human likeness increases further, the robot would again be judged as familiar or appealing.

More specifically, Mori also postulated that this uncanny valley would not only hold for the robot's static appearance, but would in fact be increased for a moving or acting robot. With the increase in interest in develop-

ing humanoid robots over the past decades, being aware of the perceptual judgments of such humanoids becomes a critical component in their development. Since the evaluation of appearance and movements of a humanoid are driven by perceptual processes, it makes sense to also use protocols from perception research to evaluate and fine-tune their effectiveness. In such experiments, typically the robot's performance is evaluated with respect to measures such as general user acceptance, recognizability of expressions, smoothness of motions, ease of interaction, duration and quality of interaction, etc. It is important that the experiment should not only be about simply asking *how good is the robot*, but it should actually tests the robot in the intended task context or that whether it uses additional, indirect measures of effectiveness. As a tutorial on designing and analyzing perceptual experiments and user studies is beyond the scope of this chapter, we refer the reader to introductory texts such as [78.7, 8]. In this chapter, we will focus on two important topics related to humanoid perception in the context of perceptual robotics: facial animation and the perceptual processing of body movements.

78.1 Perceptual Mechanisms of Object Representations

Object recognition is a fundamental visual function that is critical for many applications in robotics. Manipulation and grasping (Chaps. 36–38) require exact knowledge about the shape of the goal object that is often derived from visual sensors. Also the imitation of goal-directed movements (Chap. 77) requires knowledge about target objects. Finally, social and collective robots require robust recognition of other agents and objects which are taking part in the present action (Chaps. 71, 72). The importance of object and shape recognition for many other applied robot systems, like construction and assembly robots or smart cars (Chap. 54) is immediately evident.

78.1.1 Perceptual and Computational Basis of Object Representations

The question of how humans learn, represent, and recognize objects under a wide variety of viewing conditions presents a great challenge to both neurophysiology and cognitive research. Frameworks for explaining the amazing robustness of human recognition processes and how humans represent objects can be broadly classified into two approaches: in the model-based representation, an image on the retina is analyzed to yield three-dimensional parts of an object based on geomet-

ric primitives (cf. also Chap. 32). These primitives are then matched to an internal, three-dimensional model of the object (Fig. 78.1, bottom). Exemplar-based representation approaches assume that the internal storage consists of, typically two-dimensional, snapshot-like representations of objects, which are directly compared to the visual input via simple image transformations. In the following, we will briefly describe the basic properties of these two approaches as well as perceptual evidence for their plausibility in explaining human recognition performance.

Structural Description Models

The basic idea of structural description models is that object recognition or categorization is based on a structural representation, which is defined as a configuration of elementary object parts that are regarded as shape primitives [78.9]. Structural description models aim at supplying abstract and propositional descriptions of objects, while at the same time disregarding irrelevant spatial information. Therefore, structural description models typically predict that recognition performance is invariant regarding spatial transformations. *Biederman's* recognition-by-components (RBCs) or geon structural description (GSD) model can be regarded as the best developed example of the struc-

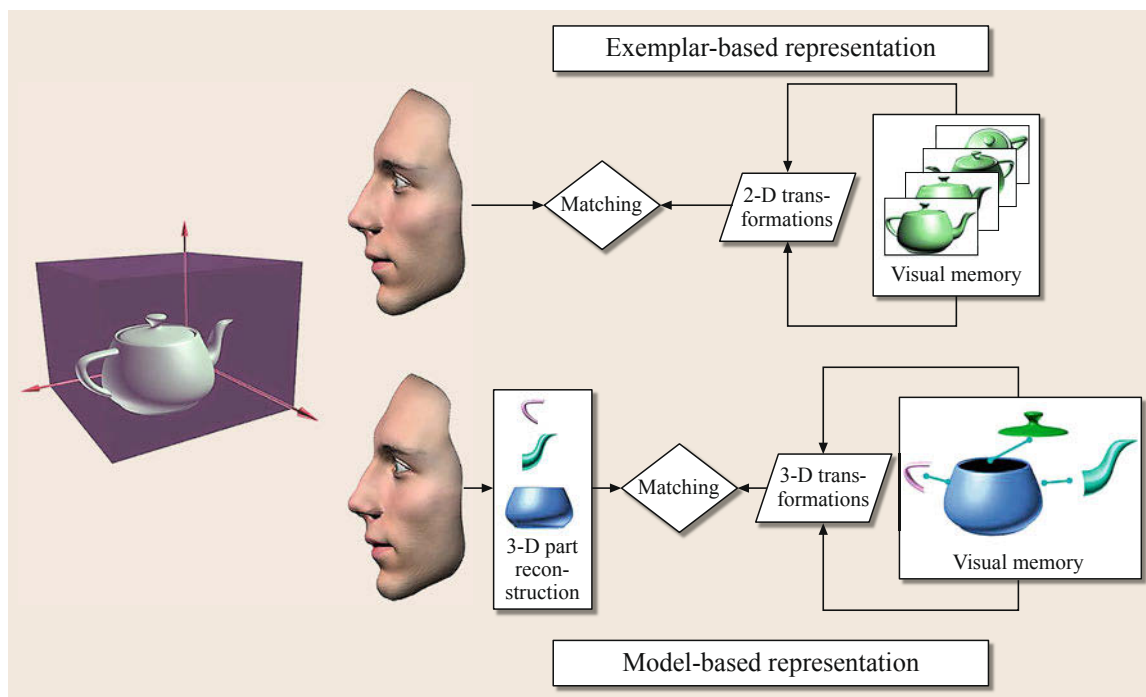


Fig. 78.1 Schematic drawing comparing exemplar-based with model-based representations. Object perception based on model-based representations assumes that the brain extracts **3-D** parts from the visual image, which are then matched to an internally stored **3-D** model of the teapot. Contrasting with this approach, object perception based on exemplar-based representations is accomplished by directly comparing stored templates or example images with the current picture of the teapot

tural description model type [78.10]. According to this model, objects are represented as configurations of elementary three-dimensional primitive parts, called geons. These geons are derived from nonaccidental properties (**NAPs**) in the image, i. e., from properties which unlikely arise by chance, and are more or less invariant over a wide range of views. For example, the properties straight vs. curved, symmetrical vs. asymmetrical, parallel vs. nonparallel are regarded as **NAPs** (**NAPs** were originally proposed within an image-based approach by Lowe [78.11]). According to the model, geons and their spatial configuration are combined into a structural representation, called **GSD**. The spatial relations between parts are described in a categorical way, using relations like above, below, etc. Like other structural description models, Biederman's model predicts invariance in relation to position and size and also in relation to orientation in depth, as long as no parts are occluded.

The question has to be raised whether objects can be decomposed into geons at all. It was argued that Biederman's **RBC** cannot be applied to a whole range of biological stimuli [78.12], or that biological shapes in general cannot be adequately described by struc-

tural description models [78.13]. This problem extends also to artifact categories like shoe, hat or backpack, which seem to exceed the scope of the geon model. Therefore it has to be doubted that object parts are necessarily represented as geons, or as similar geometrical primitives (further problems of **RBC** in [78.14, 15]). However, this does not mean that category representations do not have a part structure: in fact, it is not the notion of the part structure in object representations by itself which is problematic, but the use of parts and relations as a basis to derive invariant recognition performance [78.15].

Exemplar-Based Models

Over the last two decades, an increasing number of studies has demonstrated that recognition is not view-independent. Orientation-dependent recognition effects were found for novel objects [78.16, 17], and also for common, familiar objects [78.18, 19]. Orientation-dependent recognition performance has been shown not to be limited to individual objects, such as faces [78.20, 21], or to objects on the subordinate level of categorization [78.16, 22], but also was demonstrated for basic level recognition [78.19, 23].

Moreover, recognition performance is not only influenced by the orientation, but also by the size of the stimulus. Results are quite similar: reaction times (RTs) and error rates depend on the extent of transformation that is necessary to align memory and stimulus representation. RTs increase in a monotonic way with increasing change of (perceived) size (for a review *Ashbridge and Perrett [78.24]*). Several studies even show a systematic relationship between the amount of translation and recognition performance: Increasing displacement between two sequentially presented stimuli led to a deterioration of performance, both for novel objects [78.25] and familiar objects [78.26]. Overall, view-independent models are difficult to reconcile with these findings which indicate that recognition performance depends systematically on different spatial transformations.

In the following, we will briefly review three types of exemplar-based models, which – by virtue of different computational mechanisms and processes (including alignment, interpolation, and pooling/thresholding) – explain the transformation-dependent performance that was found in the psychophysical experiments.

In the class of alignment models, *Ullman's [78.12, 27] 3-D alignment model* and *Lowe's [78.11] SCERPO model* are probably the best-known examples. Both models work by storing 3-D models of objects, which are aligned to images by perspective projection of corresponding features (edges or feature points on the object). As an alternative to *Ullman's [78.27] model* that relies on 3-D object representations, *Ullman and Basri [78.28]* suggested an alignment model on the basis of 2-D (two-dimensional) views. In this model, an internal object model is constructed by a linear combination of a small number of stored 2-D exemplar images. Thus, the alignment is not achieved by a spatial compensation process, but by linear combination of images. The intuition behind the linear combination approach can be explained in simple terms. Suppose that two views of the same three-dimensional object are stored, taken from somewhat different viewing directions. An intermediate view can then be described as a weighted sum of the views that are already stored. In this case, the representation is based on the two-dimensional positions of corresponding features in each view. Making the set of views closer results in an object representation that is equivalent to storing a 3-D model.

In the interpolation model, recognition is achieved by localization in a multidimensional representational space, which is spanned by stored views [78.29]. The interpolation model is based on the theory of approximation of multivariate functions and can be imple-

mented with radial basis functions (RBFs). In this scheme, the whole viewing space of an object is approximated by the learned exemplar views through a limited number of series of so-called radial basis functions (such as Gaussian functions) each of which becomes activated within a limited region of the high-dimensional feature space. Object recognition then means to examine whether a new point corresponding to the actual stimulus can be approximated by the existing tuned set of basis functions. Thus, recognition does not occur by transformation or reconstruction of an internal image, but rather by interpolation or approximation of exemplars in a high-dimensional representational space.

At the end of the 1990s – and as an extension to the interpolation models – recognition models based on pooling and thresholding were developed [78.30–33]. Recognition is explained on the basis of the behaviour of cells that are selectively tuned to specific image features (fragments or whole shapes) in a view-dependent (and size-dependent) way. A hierarchical pooling of the outputs of view-specific cells provides generalization over viewing conditions [78.30]. A similar proposal was made by *Riesenhuber and Poggio [78.31]*. The threshold model [78.34] also accounts for the systematic relation between recognition latencies and the amount of rotation (and size-scaling). The speed of object recognition depends on the rate of accumulation of activity from neurons selective for the object, evoked by a particular viewing circumstance. For a familiar object, more tuned cells will be activated in the views most frequently presented, so that a given level of evidence (threshold) can be achieved fast. When the object is seen in an unusual view, fewer cells will respond, and activity among the population of cells selective for the object's appearance will accumulate more slowly. Consequently, these threshold models explain orientation-dependence without the need to postulate transformation or interpolation processes.

In a recent paper, an attempt has been made at view-dependent and view-independent approaches to object processing [78.35]. A careful study of the view-dependency of novel objects was designed by combining structural properties (number of parts) with metric properties (thickness, size of parts) has found that both view-dependent and view-independent processing seem to be combined in object recognition. Thus, instead of taking the extreme standpoints of view-based versus view-invariant processing, one might envisage a visual processing framework in which features are selected according to the current task, where the optimality, efficiency and thus the dependency on viewing parameters of the features depend on the amount of visual experience with this particular task.

Several computational models have been proposed that aim at modelling and explaining the dependence of human recognition performance on spatial transformations in its complexity. All of these models rely on storing exemplars – in the simplest form just 2-D views of objects – and matching the retinal image to these stored examples by different computational methods. The later models of recognition take their inspiration from recent findings from physiological studies concerning the functional building blocks of human vision in the brain. In the following, we will therefore briefly review the neural processing of visual information in the brain that underlies our ability to recognize objects.

78.1.2 Neural Representations in Object Recognition

Functionally, it has been shown that the flow of visual information in the brain can be divided into two major pathways: the dorsal pathway is believed to process motion and motor- or action-related visual information, whereas the ventral pathway usually is associated with the task of object recognition. The structure of the ventral pathway is hierarchically organized and consists of a series of interconnected stages that start from the retina, passing through the lateral geniculate nucleus (LGN) to the primary visual cortex (V1) and extrastriate visual areas V2, V4, and IT. The inferotemporal cortex (IT) provides input to the prefrontal cortex (PFC), which is believed to play an important role in identification and categorization of visual stimuli. Recordings in the parietal cortex [78.36] suggest, in addition, that specifically for grasping and object manipulation also dorsal regions might be centrally involved in the recognition of manipulable objects and their affordances (Chap. 77 for a more detailed discussion).

The seminal work of Hubel and Wiesel [78.37] in the cat (and later also in the macaque) visual cortex first established the idea of a hierarchical organization of visual processing. They found so-called simple cells in the early visual cortex (area V1) that responded best to bar-like stimuli at a particular orientation and position in the visual field. The response pattern of these cells could be modeled as a receptive field using Gabor-type functions. Later in the processing stream they found so-called complex cells which responded best to bar-like stimuli at a particular orientation nearly everywhere in the visual field – cells, which had become partially position invariant. This general idea of increasing invariance to stimulus properties with later stages of the processing stream has been verified in further physiological studies. In general, it has been found that the receptive field of the neurons increases and that the complexity of

the stimulus it responds also increases. One of the key studies about the functional role of IT regions has investigated the responses of neurons to real-world objects in anesthetized monkeys ([78.38]; see also Tanaka [78.39] for a review). Although some neurons were found which responded maximally to simple bar-like stimuli, the majority of neurons in posterior inferotemporal cortex (PIT) preferred complex objects such as star shapes or circles with protruding elements. Interestingly, neurons were highly sensitive to minuscule changes to these objects such as the relative orientation or thickness of the elements. On the other hand, neurons were quite insensitive to stimulus variations such as size, contrast or retinal location. These findings were taken as evidence that one of the strategies for representing objects might be to use a number of moderately complex visual elements, whose pattern of co-activation encodes the visual appearance of the stimulus. In addition, Wang et al. [78.38] found neurons in anterior inferotemporal cortex (AIT), which responded maximally to images of whole objects such as faces or cars, indicating that already in IT object specific encodings might be present. Several other studies have also found neurons in this area which are tuned to faces, parts of faces, as well as body parts ([78.40] for a review).

In another set of experiments, Logothetis et al. [78.41] found AIT neurons, which showed a strong view-based behavior for the same stimuli that were used in the study of Bülthoff and Edelman [78.16], whereas they were invariant to size and location of the stimulus. Their findings provide strong evidence that a neural implementation of view-based object encoding is possible and indeed seems to be used for recognition. In addition to view-selectivity and size invariance, the investigated cells were also found to be maximally selective for the holistic stimulus rather than its constituent parts. This finding indicates that these cells might be encoding the pooled co-activation pattern of earlier PIT cells and thus form view-tuned units of recognition. It is important to stress in this context that an abstraction such as *grandmother* neurons, which specifically encode only one stimulus, does not seem plausible. Rather, the majority of neural responses in this and other experiments showed selectivity for a number of stimuli. A plausible explanation for this finding is that objects are encoded not by a single neuron but by a population code encompassing a number of neurons, which greatly increases the robustness of the representation [78.33].

The findings from this area of research can be summarized in a simple functional architecture: going from early stages to later stages of visual processing in a feedforward fashion, feature complexity increases from simple edge detectors toward view-tuned, com-

plex object cells and invariance to changes in the stimulus increases. This functional architecture is reflected not only in the object recognition framework discussed previously, but it also provides the motivation for computational vision systems that have been developed over the last few decades which will be discussed in the following.

78.1.3 Object Recognition: Lessons from Computer Vision

Computer vision started out as a subfield of artificial intelligence in the 1960s. Early work on scene understanding by *Roberts* [78.42] showed how computers could *parse* worlds consisting of simple, geometric objects such as cubes, pyramids, etc. The main thrust of computer vision systems in the following decades consisted of building algorithms for reconstructing a three-dimensional world from images – this development was further stimulated by *Marr's* very influential theory of vision as 3-D reconstruction [78.1]. This theory was built on extracting geometric primitives from images that could be mathematically described as generalized cylinders. Although the mathematical rigor of such approaches was very appealing, computational implementations turned out to have strong limitations. Extracting robust features is a necessary prerequisite for building a 3-D reconstruction of the image, and finding these features proved to be hard under real-world conditions due to the enormous amount of variation in the image caused by changes in lighting, depth rotations, noise, occlusion, etc.

Parallel to the paradigm shift in human psychophysics and physiology, exemplar-based computational systems began to emerge, which for the first time showed good recognition performance under a larger range of viewing conditions. These recognition systems were based on – sometimes surprisingly simple – histograms of pixel values [78.43], local feature detectors [78.44, 45] or on a straightforward pixel representation of images using principle components analysis [78.46]. All of these recognition systems relied on a database of labeled example images, an algorithm for extracting features from these images, and a suitable classification method for comparing sets of image features.

Returning to the discussion of modeling human vision, in the following we provide an exemplary review of three neuromorphic recognition systems that are based on a functionally plausible, exemplar-based architecture: these are SpikeNET [78.48], LeNet [78.49], and a framework by *Serre et al.* [78.50]. The first system is motivated by the finding that humans are amazingly fast at categorizing images as containing an animal or

a face [78.51]. Typical response times for this task are so small (on the order of 100 ms) that the visual signal has only time for one feedforward pass through the visual areas of the brain (Fig. 78.2) – any recurrent feedback processing would necessarily delay the decision and therefore result in longer response times. Based on this finding, a neural network architecture was designed [78.48] that exploits the timing of neuronal responses (spikes) to encode visual signals using a *who fires first* – strategy. This is different from traditional neural networks in that the timing is used rather than the firing strength. An object in this system will therefore be represented by an ensemble of neurons that represents a pattern of spike responses from earlier low-level, feature extraction neurons. In their implementation, these low-level neurons consist of standard Gabor-type receptive fields that are similar to the receptive fields found in the cat's visual cortex [78.37]. This spike time encoding allows for very fast processing of visual stimuli and has been shown to provide robust recognition results. The network ar-

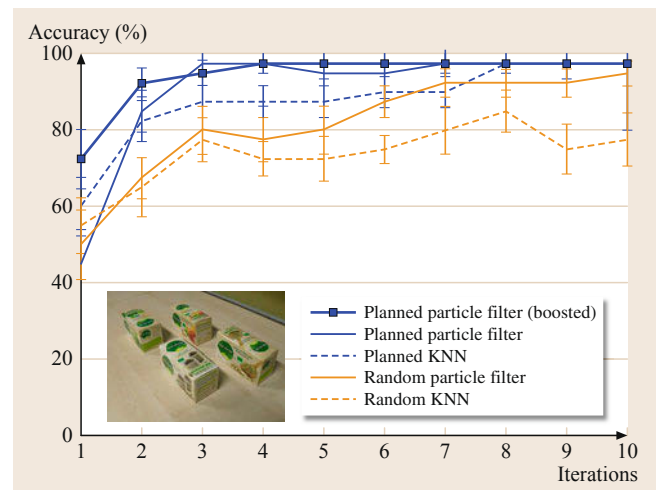


Fig. 78.2 Recognition performance of four highly similar object (shown in the inset) by an in-hand recognition system using active view selection (after [78.47]). The five methods compared in the plot contrast planned (blue) and unplanned (orange) exploration of the objects in the hand of the robot. The x-axis is the number of iterations, and the y-axis is the recognition accuracy in percent. As time (or iteration number) proceeds, the planned approaches surpass random exploration significantly. In addition, employing probabilistic methods for recognition of the objects using a particle filter also provides a recognition improvement. Finally, the *thick, solid blue line* shows performance in a system which boosts the likelihood of an object given the current visual evidence in the particle filter framework – this approach fares best overall. These results show that active view selection enhances the robot's ability to learn and recognize objects in real-world environments

chitecture LeNet [78.49] consists of a neural network that uses a hierarchy of layers of trainable convolutions and spatial subsampling, as well as nonlinear filtering to extract features of increasingly large receptive fields, increasing complexity, and increasing robustness. Using extensive, supervised training of the full hierarchy, such a network provides a very efficient, sparse set of features for many visual recognition tasks. Finally, the network architecture by *Serre et al.* [78.50] uses a very similar hierarchical structure of layers in which feature complexity and invariance are successively increased by linear and nonlinear pooling – its lower level feature detectors, however, are trained in an unsupervised fashion on a large database of natural images, yielding a large set of detectors that are optimally tuned to natural image statistics. Again, the performance of this model in recognition tasks has been shown to be very good – in addition, comparisons with physiological and psychophysical experiments have shown that this framework is also capable of modeling human results from these experiments.

Recent research has mainly focused on two topics: the automatic extraction of optimal visual features for efficient recognition and categorization, and the extension of the frameworks for providing invariance against changes in viewing conditions (such as rotations in depth, scaling, translation, illumination, and occlusion, for example, *DiCarlo et al.* [78.52], *Rolls* [78.53] for discussions of invariance in neuromorphic architectures). In a recent paper [78.54], these two issues have been addressed in a face recognition task conducted on a difficult database of faces taken in uncontrolled environments. The selection of optimal features was done by evaluating a large set of potential visual feature combinations using GPU-accelerated algorithms. The issue of invariance was addressed by using a hierarchical, multilayer model in which each layer includes linear and nonlinear pooling operations that encode the input image. The combined system was benchmarked against other standard feature-extraction methods and a *flat*, nonhierarchical one-layer model. Both properties resulted in increased recognition performance on the database outperforming other benchmarked state-of-the-art methods. In addition, the system also showed increased robustness against viewing variations, which included pose, position, scale, and background clutter.

In summary, neuromorphic architectures have now reached a stage of maturity that can put them even ahead of sophisticated, state-of-the-art computer vision frameworks. The ability to learn and adapt the feature set to viewing conditions and the increased robustness to viewing conditions makes such architectures good candidates for building the visual learning and recognition system for a perceptual robot.

78.1.4 Object Learning and Recognition for Perceptual Robotics

In general, it can be said that the success of perceptually inspired recognition systems can be seen as a strong indicator for the feasibility of a data-driven, exemplar-based approach to recognition. There are three issues, however, which so far have not been addressed in any of these vision systems and which will be important both for achieving human performance in generic recognition tasks in a perceptual robotics application – as well as for a full understanding of the processes in human object recognition.

First of all, all of the above-mentioned systems are feedforward – virtually no feedback, recurrent processing is implemented in their architecture, which makes them in a sense very similar to the simpler frog- or bee-like neural systems discussed in Chap. 77. Although there is evidence that humans solve some recognition tasks using very little feedback (see, e.g., *Thorpe et al.* [78.51]; *DiCarlo et al.* [78.52]), it nevertheless is a crucial component of visual processing driving, for example, attentional focus, context awareness, as well as memory and reasoning processes – basically everything that makes up visual *intelligence*. Some visual attention models that are relevant for robotics systems are reviewed in Chap. 77.

Secondly, a severe limitation of most of today's artificial recognition systems is that they solely focus on the static domain of object recognition. Visual input on the retina, however, consists of dynamic changes due to object- and self-motion, nonrigid deformations of objects, articulated object motion as well as scene changes such as variations in lighting, occluding, and re- and disappearing objects – where at any given point in time several of these changes can be interacting. Several psychophysical experiments, indeed suggest an important role for dynamic information, both in learning and recognition of objects [78.55–58]. These results ask for an extension of current object recognition frameworks with a temporal component in order to arrive at truly spatiotemporal object representations. Combining methods from computer vision, psychophysics, and machine learning, *Wallraven and Bülthoff* [78.59, 60], have developed a framework that fulfills this requirement and learns spatiotemporal, exemplar-based object representations from image sequences. More specifically, spatiotemporal characteristics of the visual input are integrated into a connected view-graph representation based on tracked local features. In order to provide robust classification performance, machine learning techniques are used to design efficient methods for combining support vector classification schemes with these local feature representations [78.61]. In sev-

eral studies it was shown that the framework achieved excellent recognition results on both highly controlled databases as well as on real-world data. The integration of spatiotemporal information provides characteristic information about dynamic visual input via the connection of views and the two-dimensional image motion of discriminative features. In addition to delivering good recognition performance, the framework was also able to model results from psychophysical experiments on face and object recognition. A similar model using a neuromorphic architecture integrating the temporal dimension was proposed by Kietzmann et al. [78.62].

A third issue that – in our view – will be essential for designing and implementing efficient perceptual robots consists of the multisensory nature of our perceptual system (see also the discussion of embodied robots in Chap. 13). As an example, there is a close coupling between the human visual and haptic system – touch can provide a wealth of complementary information about an object when it is manipulated, such as its texture, its shape, its position in space relative to our body, etc. In a series of psychophysical experiments [78.63], participants had to learn views of four simple, 3-D objects made of stacked toy-bricks either in the haptic modality (when they were blind-folded) or in the visual modality (without being able to touch them). Subsequently, they were tested both within the same modality as well as across modalities. Recognition results showed that cross-modal recognition is possible well above chance. Not surprisingly, recognition of rotated objects in the within-modality condition was severely affected by rotation in both modalities. This shows that not only visual recognition is highly view-dependent but also that haptic recognition performance is directly affected by different viewing parameters. The results from this experiment thus support the view that haptic recognition is also mediated by exemplar-based processes.

Taken together with the keyframe framework outlined above, this cross-modal transfer might be an important reason for the excellent visual performance

of human object recognition – after all, it is known that infants learn extensively by actively grasping and touching objects, which thus could provide a *database* of object representations for visual recognition [78.64]. Using this basic perceptual principle as a motivation [78.60] have applied an extension of the keyframe framework in an online robotics scenario for efficient learning and recognition of multisensory object representations. More specifically, a framework was developed to integrate both proprioceptive information originating from haptic sensors in the robot's hands and visual information coming from the robot's cameras. For this, the robot would perform an exploratory movement with an object in its hand (such as turning it and looking at it from all angles) and from the resulting image sequence learn spatiotemporal, view-based representations using the keyframe framework. Each view of this representation, however, is also linked to the current proprioceptive state (i. e., the joint angles of the hand at that point in time) and therefore provides an anchor into a hand-centered, three-dimensional space. In this way, a representation is generated that links perception and action. The proprioceptive information can then be used as an additional constraint for both learning of objects and recognition of objects and was shown to provide increased robustness compared to visual matching alone. The framework was also used as the basis for recent work in which a humanoid robot (the iCub) performed active in-hand object recognition, searching for the optimal view that allowed it to disambiguate the object currently held from other, previously seen objects [78.47]. Again, linking the exploratory actions (turning the hand) with the visual data resulted in a much faster and more reliable object recognition performance. Sample data comparing unplanned and planned recognition of difficult objects is shown in Fig. 78.2 ( VIDEO 569).

Such approaches pave the way for a view of recognition as an active, multisensory process in which rich, extensible object representations are formed and improved over the life-time of the robot.

78.2 Perceptual Mechanisms of Action Representation

The recognition of complex movements and actions is fundamental for many applications in robotics, such as imitation learning by observation. Interactive robots need to analyze their users' movements in order to respond in a natural way to their social and emotional behavior (Chap. 72). The following section reviews what is known about movement and action recognition in the brain and tries to highlight a few aspects that have

or might be successfully transferred to biologically inspired applications in robotics and computer vision.

78.2.1 Recognition of Complex Movements and Actions in Primate Cortex

The recognition of complex movements and actions is a fundamental problem for higher animals and specif-

ically for primates. While simple movement patterns are sufficient for eliciting stereotypical prey catching behavior in simple vertebrates ([78.65]; see also Chap. 77), higher animals exploit more complex movement patterns, e.g., for the recognition of conspecifics or predators, or for communication by facial movements, gestures, or body expressions. Human perception of body motion patterns is very efficient, even for extremely impoverished stimuli. This has been demonstrated in classical experiments by *Johansson* [78.66], who showed that complex dynamic actions can be recognized even from displays that consist only of a small number of dots moving like the joints of a human actor. Subsequent research has demonstrated that humans can extract highly specific information from such *point-light displays*, e.g., the gender or the identity of people. To our knowledge, no technical system for motion recognition has been proposed so far that accomplishes a comparable level of robustness. While much more research in neuroscience has been dedicated to object recognition (Sect. 78.1.2), some studies have tried to uncover neural [78.67–70], and computational principles [78.71–73] of visual movement recognition. Some of these principles have been transferred to the construction of systems in computer vision and robotics.

Neurophysiological and brain-imaging studies indicate that the recognition of facial and body movements involves the ventral and the dorsal visual pathway. This implies that likely form and optic flow information are integrated during the processing of action stimuli in visual cortex. The ventral pathway, which is specifically responsible for the processing of form information has been discussed already in Sect. 78.1.2. Like the ventral stream, also the dorsal pathway is hierarchically structured, and the size of the receptive fields of the neurons increases along the hierarchy. Some cortical areas that are part of the dorsal pathway are listed in Fig. 78.3. The *medial temporal area* (MT) contains neurons that are selective for simple local motion and coherent motion. On higher levels of the dorsal stream, e.g., in the *superior temporal sulcus* (STS), neurons that are selective for hand and body movements and for facial expressions have been found in monkeys [78.69], and similar structures are activated by these stimuli in the human brain. In addition, areas selective for human body shapes, such as the *extrastriate body part area* (EBA), likely to contribute to the recognition of actions [78.74], where information of form and motion features seems to be integrated on higher processing levels [78.73].

For the recognition of goal-directed actions, such as reaching or grasping, in addition cortical structures beyond the visual cortex, such as the parietal and premotor cortex, seem to play a critical role. The role of these

structures for action recognition has been analyzed in particular in the context of the study of the *mirror neuron system* [78.75]. Mirror neurons are sensorimotor neurons that combine visual tuning during action observation as well as selective motor tuning. Areas in parietal cortex, such as the anterior might be specifically relevant for the recognition of action-related objects and their relationship to moving effectors [78.36]. Research about the mirror neuron system has influenced the construction of a whole generation of biologically inspired robots (Chap. 77). The guiding hypothesis has been that the visual recognition and *understanding* of actions is accomplished by mapping of observed body movements onto motor representations that are relevant for the execution of the same type of action.

78.2.2 Biological Principles with Relevance for Computer Vision and Robotics

We discuss in the following two major principles that have been derived from the analysis of action recognition in biological systems that have been transferred to technical applications in computer vision and robotics.

A first principle that seems to be implemented in movement recognition in primate cortex is a hierarchical architecture of feature detectors, which accomplishes action recognition by the detection of temporal sequences of relevant motion and form features. Such detection does not necessarily require the reconstruction of the three-dimensional facial or body shape, nor an exact simulation of the dynamics of the underlying movements. Instead it can be accomplished by much simpler computational mechanisms. Like object recognition, the recognition of complex motion patterns is strongly orientation- and view-dependent. This property has been observed at the level of individual neurons in the STS, and for the activation of biological motion-selective areas in human cortex [78.69] as well as for action-selective neurons in higher areas such as the premotor cortex [78.76]. View- and orientation dependence seem compatible with an encoding of visually perceived movements in terms of potentially learned example views, or *keyframes* (snap shots), and of instantaneous optic flow patterns that are characteristic for actions [78.67, 73]. While there might be some innate preferences for specific features [78.77], psychophysical and fMRI (functional magnetic resonance imaging) experiments suggest an important role of learning in visual movement recognition [78.78–80]. For example, subjects can learn easily to recognize individually – specific body and facial movements [78.81, 82]. Learning-based theoretical models, exploiting similar principles as neural object recognition models, account for a variety of experimental data on action

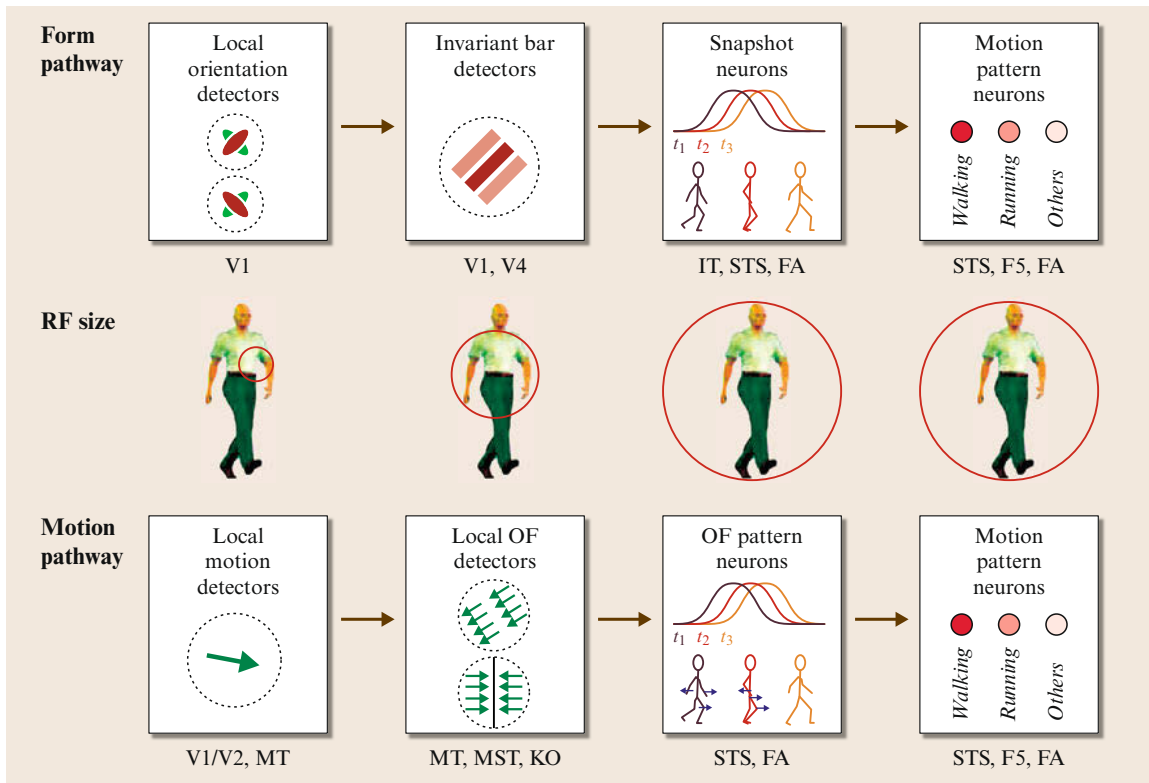


Fig. 78.3 Example-based neural model for the visual recognition of body movements that integrates the processing of form and motion features in the ventral and dorsal visual pathways (after *Giese and Poggio* [78.73])

recognition in biological systems [78.73, 83, 84], also supporting a central role of learning.

As an example of such a learning-based architecture, Fig. 78.3 illustrates a hierarchical model for the recognition of complex body movements [78.73]. It consists of two hierarchical streams modeling the ventral and the dorsal visual pathways, which contain detectors for action-specific motion and form features. The form pathway of this model is similar to the object recognition models described in Sect. 78.1.2. The motion pathway of the model contains detectors for action-specific optic flow features with different complexity. Like for the described object recognition models, position, and scale invariance is accomplished by appropriate nonlinear pooling of the responses of detectors with different spatial and scale selectivity along the hierarchy. In addition, the model contains recurrent neural circuits that make the responses of the recognition neurons selective for temporal order. In this way the model responds only to actions that are executed with the correct temporal order, and also with approximately correct speed. The underlying network dynamics can be interpreted as a neural implementation of a Markov model, where the present recognized pattern predicts

possible future patterns (Chap. 68). A strong activity in the network emerges only when the stimulus sequence matches these predictions.

Similar hierarchical neural architectures inspired by the visual cortex have been used in the context of mirror-neuron robot systems [78.85, 86]. In addition, recent work in computer vision shows that such biologically inspired architectures can reach very high performance levels, comparable to state-of-the-art algorithms in computer vision [78.87–89].

A second principle of movement recognition, which has been discussed extensively as basis for the recognition of imitable actions, and as explanation of the function of the mirror neuron system [78.75] is the idea that action observation is based on an internal simulation of the observed motor behavior. A variety of computational models for action recognition by internal simulation have been proposed in the neuroscience literature, e.g., exploiting feedforward controllers [78.90], coupled forward and backward models [78.91], hierarchical Bayesian predictive models [78.92], or a free energy minimization framework [78.93]. (A further more extensive discussion about theoretical models for the mirror neuron system with relevance for robotics

can be found in Chaps. 68 and 77.) A main difficulty of the recognition of actions by internal simulation of associated motor behaviors is the accurate estimation of relevant geometrical quantities from image data, especially when no special depth sensors or even online motion capture are available. Many of the underlying motor control models are formulated in joint angle space, and the robust recognition of joint angles from monocular videos is known to be a difficult computer vision problem, which so far is solvable only for highly restricted classes of movements with strong learned priors, and at considerable computational cost [78.94, 95]. This raises the question about simpler computational approaches for the recognition of goal-directed actions, which explain biological data and might be interesting for technical applications.

A recently developed model for the visual recognition of goal-directed hand actions in cortex that follows these lines [78.96] is illustrated in Fig. 78.4. The underlying architecture is an extension of the form pathway of the model shown in Fig. 78.3, by the addition of neural circuits that process the spatial and temporal relationship between the observed effector (in this case the hand) and the recognized goal object (e.g., a grasped object). The model works, exploiting a purely exemplar-based approach (Sect. 78.1.1), without explicit reconstruction of the three-dimensional structure of the object or the effector. The model comprises three modules: The first module (A, in Fig. 78.4) recognizes shapes of the goal object and of the effector,

implementing a shape recognition hierarchy similar to standard object recognition models as the ones described in Sect. 78.1.3. The analysis of the temporal deformation of the hand is based on the recognition of sequences of key shapes, like in the form pathway of the model in Fig. 78.3. Opposed to standard object recognition models, however, the highest level of this shape recognition hierarchy is not completely position-invariant. Rather, it retains coarse position selectivity by implementing multiple replica of the same shape detectors that are selective for different image positions. This makes it possible to further analyze the spatiotemporal relationship of the recognized goal objects and effector. This analysis is realized in the second module (B) whose core is formed by two-dimensional *relative position maps*. These are neural activity maps that represent the effector position as activity peak in a two-dimensional coordinate system that is centered on the object position in the image. These maps are computed by a gain fields [78.97] that multiply the output activities of shape selective neurons with selectivity for object and effector. The activity distribution in these neural map is analyzed by *affordance neurons* that are activated only when hand and object shape match and are in a spatial relationship that is suitable for a successful grip. By appropriate pooling of the responses of motion energy detectors that receive input from the relative position map *relative motion neurons* can be constructed, whose activity characterizes the relative motion between the effector and object

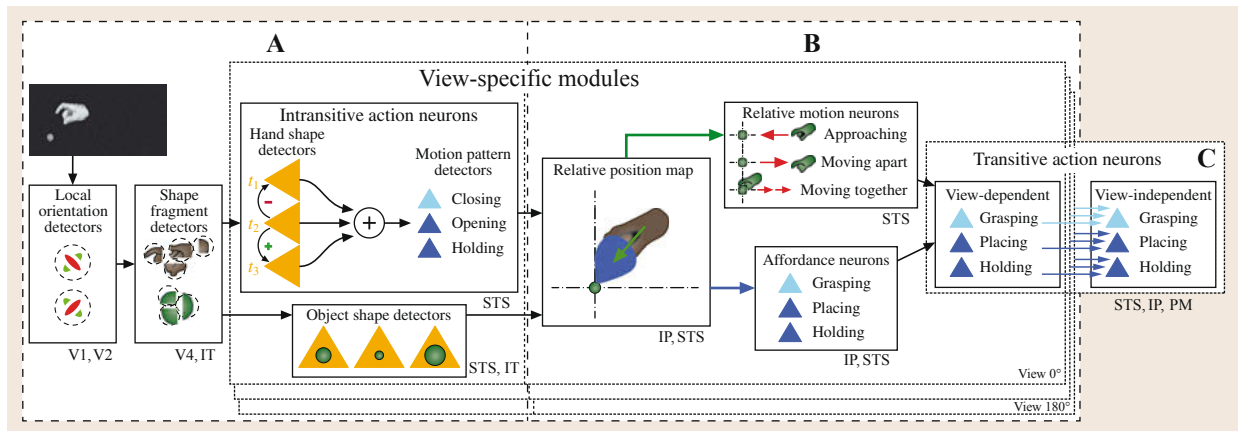


Fig. 78.4a–c Physiologically inspired model for the recognition of goal-directed hand actions. The shape-recognition (a) recognizes the shape of goal objects and the shapes of individual hand postures, retaining some coarse position information. The module (b) associates the information of hand and object by computing maps that represent the relative positions of hand and object in image coordinates. From these maps the spatial matching hand and object and their relative motion can be computed. The highest level module (c) contains model neurons that are selective for different types of goal-directed actions. Up to this level the model recognizes actions in a view-dependent manner, and only at the highest level (view-independent transitive actions neurons) the model accomplishes view independence by pooling the outputs from view-specific modules (courtesy of *Fleischer et al.* [78.96])

(e.g., the hand approaching the object). The outputs of affordance and the relative motion neurons are integrated in the third module (C), which contains only neurons that are selective for visually observed goal-directed actions. This integration of information is first accomplished in a purely view-specific manner. View independence is not established until the very last hierarchy level of the model that contains view-independent action-selective neurons. The idea of establishing view-dependence only very late in the cortical hierarchy seems counter-intuitive, and is at odds with several established computational models for action recognition. However, this dominance of exemplar-based representations until very high levels of the cortical processing hierarchy has been observed in electrophysiological experiments studying mirror neurons in premotor cor-

tex [78.76]. In this structure, which is traditionally associated with motor planning, the majority of mirror neurons is view-dependent and only a minority is view-independent. The discussed model can recognize hand actions from gray level videos. It could be augmented by integration of disparity or depth features, and by appropriate attentional control mechanisms that would make it more robust to cluttered scenes with multiple relevant objects. Whether similar architectures have advantages for the robust visual recognition of goal-directed actions in technical systems remains to be shown. Very recent work shows that such hierarchical deep architectures, which consist of learned feature detectors, outperform classical technical solutions on actual computer vision benchmarks for action detection [78.98].

78.3 Perceptual Validation of Robotics

Successful human–robot interaction is perhaps easiest when the robot offers interaction channels that are compatible to that of human–human interaction [78.99]. The most important interaction channels in this case are verbal and nonverbal communication with the face. Importantly, in human–human interaction, nonverbal communication using facial expressions, for example, constitutes up to 30% of the communicative content. Facial expressions are not only used to convey someone’s mood and emotion [78.100], but are also used in communicative contexts to signal understanding (a nod of the head), to modify what is being said (a raise of the eye-brows), and to control the conversational flow (a look of confusion may signal to the speaker to repeat what has been said). Hence, many humanoids have incorporated more or less sophisticated heads capable of producing human-like facial expressions and movements. Traditionally, this has been achieved using mechatronic implementations in which actuators drive facial features directly (e.g., as in the MDS robot by Lee and Breazeal [78.101]), or – in more complex implementations of android robots – mimic human muscle movements that are then used to deform artificial skin [78.102–104]. Other systems have used LEDs for displaying simple, changeable facial features (e.g., as in the iCub platform [78.105].

78.3.1 Realistic Faces for Robots

With such a great variety of robot systems also comes the need for an investigation of their perceptual evaluation and their interaction capabilities ([78.106] for such a study in the context of facial animations in

computer graphics). Indeed, one particular problem of android, human-like systems is that they easily could suffer from the uncanny valley effect as the actuators and/or the control framework cannot easily reproduce the smoothness of human facial expressions. A study of morphed images between a nonhuman robot face and a highly realistic android robot head, for example, clearly showed evidence of the uncanny valley effect [78.107] – a similar study for moving robot faces yielded more mixed results, but still showed that the most realistic robotic faces were clearly perceived as different from that of a human talking [78.108]. One solution for this is to change the robot’s appearance such that it stays away from close human likeness; however, conveying the full breadth of human communicative signals with different facial features, or a different facial topology may also be problematic. A different solution consists of avoiding a mechanical solution and instead resorting to facial animation from computer graphics. One example of such a system was presented in Delaunay et al. [78.109] in which facial animations are projected onto a rigid face mask. Since facial animation techniques are in many ways much more advanced, such a system allows for a more realistic and flexible interaction in human–robot interaction. Subtle cues such as eye-gaze, wrinkles, and other nonrigid facial deformations could be displayed via projection of an advanced facial animation engine. Initial perceptual experiments with such systems [78.109, 110] have yielded promising results. However, more studies need to be done to assess the properties of human–robot interactions in these and other implementations of facial displays.

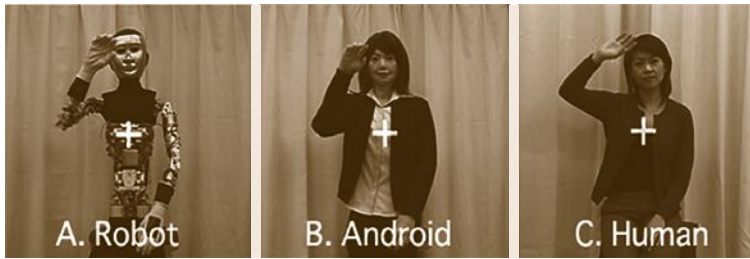


Fig. 78.5 Stimuli used in experiment investigating the fMRI correlates of the observation of human and robot movements. The neural responses to the movements by a real human are compared with the ones induced by a human-looking robot (Android), and by a nonhumanlike robot (Robot) (after Saygin et al. [78.111])

78.3.2 Perceptual and Neural Processing of Body Movements of Robots

Research in humanoid robotics finally aims at optimizing the perceived naturalness or *human-likeness* of generated robot movements, since this in the long run will increase the acceptance of humanoid robots in social contexts. However, the present humanoid platforms have typically substantial constraints that still prevent the realization of complex really human-like movements. This is even more the case for the realization of behaviors on bipedal robots, due to the difficult problem to maintain dynamic balance (Chap. 67). Therefore, most body movements realized by present humanoid robots still differ in many aspects from human movements. This makes the quantification of the degree of realism of such movements presently a less pressing topic than the field of computer graphics, where psychophysical studies for the validation of the realism and quality of computer animation methods are meanwhile a standard [78.112–114]. However, research in psychophysics and neuroscience has started to investigate the differences between the perceptual processing of human and robot movements, and interesting results have been obtained that localize cortical subsystems that might be essential to distinguish human and nonhuman robot movements. A typical question in these studies has been which critical properties determine whether visual stimuli produce *motor resonance*, or an activation of action-selective neural structures. The results of such studies have not been completely consistent, since some studies found decreased activation of action-selective networks for robot movements [78.115–118] while others found no such differences [78.119]. Primarily visual processing areas responded sometimes more for robot movements than for normal human [78.111, 117].

The problem of such studies is that many factors might influence the perception and neural signals in action-selective areas, such as form, kinematics, and optic flow patterns. Typically, it is very difficult to control these parameters separately for real robots. In addition, the learning experience of observers with the specific robot might play an important role [78.120]. A recent study by Saygin et al. [78.111] tried to separate at least the influences of the robot appearance (shape) and the motion kinematics by comparing the fMRI signals (using an adaptation paradigm) driven by three different stimuli (Fig. 78.5): a real person (that served as model for the building of the robot), the human-like looking robot (*android*), and the robot without skin and surface parts that made it look human-like (resulting in very similar motion as the full robot). In visual areas (e.g., the extrastriate body area) the human and the human-like robot stimulus result in very similar activity. This is not true for the parietal cortex, which is part of the *mirror neuron network*. This region shows large differences between the human-like robot and the other two conditions, potentially reflecting an increase of neural processing resources that are required to cope with the contradiction between the form and the kinematic information that is presented by this stimulus. Opposed to this, the not human-like robot makes it expected that the motion is also not human-like, potentially causing no such conflict. Future studies of similar type, controlling for the different information channels of action processing (Sect. 78.2.2) as well as for the predictability of such stimuli dependent on previous learning, potentially combined with quantitative neural modeling, will be required to really understand how different factors are integrated in the neural processing of robot movements, and how this causes different levels of perceived *human-likeness*.

78.4 Conclusion and Further Reading

In this chapter, we have presented several principles derived from high-level cognitive processing in vision in the human brain that have been fruitful for

the development of systems in robotics and computer vision. The recognition of shapes and complex movements and actions is an important problem for many

applications in robotics. We have discussed a variety of results from neuroscience that indicate that these brain functions are likely realized by example-based representations. We have discussed neural implementations of such representations which partially have been tested successfully in the context of technical applications, and which are strongly inspired by the real cortical neural architecture. In addition, we have presented some new computational principles that seem to emerge from recent experimental results on the representation of goal-directed actions. Finally, we have discussed work that tries to use psychophysical and neuroscience methods for the validation of the appearance and the movements of human-like robots, and for the investigation of underlying neural mechanisms.

Example-based mechanisms for object and motion recognition account for the invariant recognition of complex patterns. However, they do not automatically extract the metric information about the object geometry, position and the spatial parameters of complex trajectories in world coordinates. For some tasks in robotics, like grasping, manipulation, or obstacle avoidance, such information is required (Chaps. 36–38, 47). For such tasks, example-based recognition must be fused with methods for the extraction of the relevant metric information. In robotics such information can be extracted by stereo vision or using special sensors,

like laser range finders. In the brain the fusion between such spatial information and information about objects occurs likely in parietal areas, like the anterior interparietal area (AIP) [78.121]. However, it is unclear whether the information about objects is only represented in terms of 2-D example views. Instead, it seems likely that also some form of 3-D information is encoded, potentially in an example-based manner. Also haptic and visual information about object shape might be merged in higher brain areas, e.g., in parietal and fusiform areas [78.122]. A further discussion about biologically inspired models for the extraction of action-relevant geometrical information in the context of grasping and manipulation is given in Chaps. 32 and 77.

The perceptual validation of the human-likeness and affective impact of humanoid robots likely will become increasingly important along with the further development of the technology that will increase the level of similarity between humanoid robots and humans. Likewise, it seems increasingly important to use quantitative methods from perception science to investigate the quality of the emotional and social interaction between robots and humans. We expect this to be a field where psychology can really contribute quantitative methods to engineering, reaching a level that goes beyond a qualitative and subjective comparison of *demos* which partially is still the standard in the field of humanoid robotics.

Video-References

 **VIDEO 569** Active in-hand object recognition
available from <http://handbookofrobotics.org/view-chapter/78/videodetails/569>

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