

EXHIBIT 1013



Data Fusion Techniques for Object Identification in Airport Environment

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Abstract

Airport environments consist of several moving objects both in the air and on the ground. In air moving objects include aircraft, UAVs and birds etc. On ground moving objects include aircraft, ground vehicles and ground personnel etc. Detecting, classifying, identifying and tracking these objects are necessary for avoiding collisions in all environmental situations. Multiple sensors need to be employed for capturing the object shape and position from multiple directions. Data from these sensors are combined and processed for object identification.

In current scenario, there is no comprehensive traffic monitoring system that uses multisensor data for monitoring in all the airport areas. In this paper, for explanation purposes, a hypothetical airport traffic monitoring system is presumed that uses multiple sensors for avoiding collisions. The referenced system employs multiple types of sensors for object data collection in different situations, wherein the collected multi object data is combined to classify and identify the objects, and identified objects are accurately tracked for collision prediction.

This paper discusses a data fusion model of multisensor data for object identification in an airport environment to allow the traffic monitoring system to determine the shape, type and position of an object. As a future scope of this paper, the object shape, type and position data from the object identification stage is provided as input to the next stage in the airport traffic monitoring system to track the object movements for collision prediction. Multiple type sensors are arranged in different configurations such as complementary, competitive and cooperative arrangements. Data from these sensors is combined for object detection and identification. Optimal fusion model and object model mapping algorithms are discussed for the object identification purpose. A case study of the competitive sensor data fusion is also discussed in this paper.

Keywords

Data fusion, Object Detection, Object Identification, Object Classification

Introduction

In spite of advancements in technologies and safety solutions being incorporated into airspace and ground segments, accidents in airport ground and airspace areas are increasing due to ever increasing air traffic and human factors in the airport. In such an airport environment, for any computer vision based airport traffic monitoring system, knowledge of all objects both static and moving, classification and identification of these objects, establishing spatial and temporal relations between these objects are necessary. Many sensors have to be part of this system and multiple sensor fusion needs to combine information from different views of the environment. Hence, the accurate detection, classification and identification of these objects become a critical aspect of the airport traffic monitoring system. This paper is organized as follows:

- Scope and use of this solution
- Description of the solution
- Case Study on data fusion
- Future scope of the solution

Scope and Use of This Solution

The proposed solution discussed later in this paper is part of the hypothetical system described in the below paragraph. This hypothetical system is referenced only for explanation purposes and is not in the scope of this paper.

The hypothetical system is a computer vision based Airport Traffic Monitoring System [1], which is an integrated solution that provides a novel, comprehensive and robust solution. Technologies employed for this solution are multiple sensor data fusion for estimation and prediction accuracy, advanced image processing techniques for detecting and identifying objects, real time processing of huge data to seamlessly detect collisions in all the zones of the airport environment, advanced synthetic vision for situational awareness and communication interfaces for generating alerts and guidance to prevent the collisions. The solution covers collision detection of all phases of flight in an airport environment compared to the existing

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independent or standalone systems that cannot cover all phases of flight. The system functions monitor for collision threats in all phases of flight and provide timely alerts in order to avoid the collisions.

The hypothetical system's execution flow consists of four stages. Fig. 1 shows four stages of processing: data acquisition and storage, data processing, synthetic visual 3D simulation and advisory and control communication. The encircled portion indicates the stage in which the proposed solution is integrated into the hypothetical system.

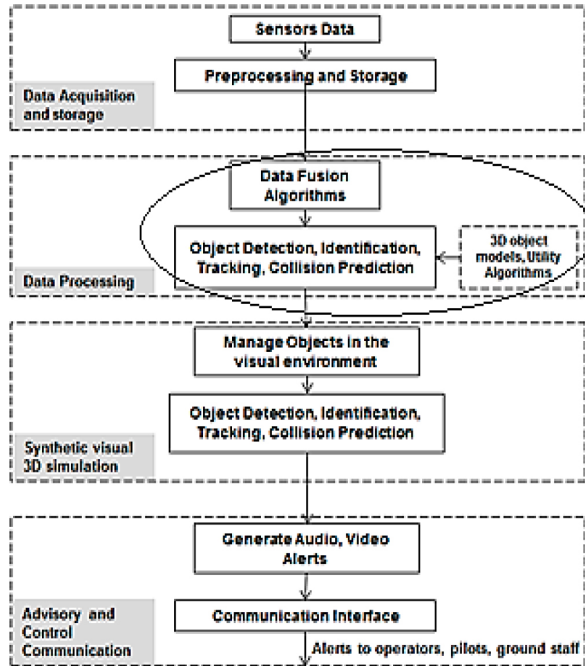


Fig 1. Data fusion and Object identification stage in the hypothetical computer vision based Airport Traffic Monitoring System

Description of the solution

This solution proposes data fusion techniques for object detection and classification using multisensor data for accurate identification of the movable objects in an airport environment in all weather conditions. Sensors are positioned in multiple traffic zones of the airport environment to capture the moving object features. Various diverse features from these sensors are then combined to form useful data sets for object detection and classification.

Multi Sensor Consideration

Data from a single sensor has limitations in terms of field of view, image loss due to occlusions, weather and visibility conditions. Hence, there is need for combining information from different views of the environment using heterogeneous multi sensors to obtain more accurate object detection and identification.

There is no single type sensor capable of sensing all the measurements that are needed to precisely perceive the environment in object detection and identification applications. Day vision and infrared cameras are used to periodically capture image frames from good and poor visibility conditions. LIDAR sensor is used for capturing the range and shape of the object. Range, velocity and

angle information is captured from Radar. Table 1 summarizes the features that can be tracked for this application and drawbacks of each sensor.

Table 1. summarizes the features that can be traced by different sensors and their drawback.

Sensor Type	Tracking Features	Drawback
LIDAR	Edge target, Range	Higher cost and affected by weather
Video Camera	Vision target (edge, patches, gradients)	Limited depth perception and distance; affected by weather
Infrared Camera	Vision target (edge, patches, gradients)	Non-thermal signatures cannot be detected
Radar	Point target, Range	Limited information about object, higher cost

Sensor Network Configuration

LIDAR and camera sensors provide features that can be used to infer appearance information of objects. Intelligently combining these features from sensors gives a complete view of the objects and the environment around. Camera sensors can be used to capture the appearance of objects using features like edges, intensity, textures or shapes. Camera data is sensitive to frequent changes in the ambience. LIDAR can provide complementary or redundant information such as position and shape to deliver a set of discrete points of impact on static and moving objects.

Sensors are generally arranged in three different configurations [2]: complementary, cooperative and competitive as shown in Fig 2.

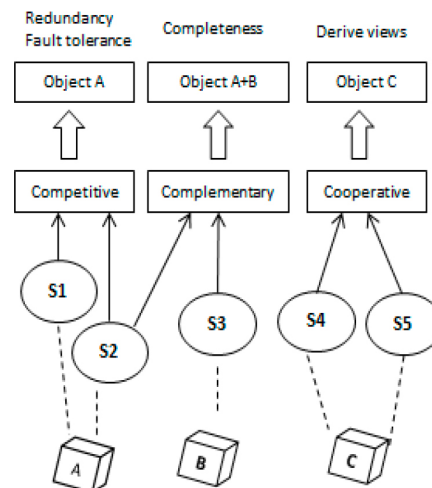


Fig 2. Sensor network configurations

In complementary type configurations, each sensor (S2 and S3) views one part of the region and combining them gives complete view of the entire region. In competitive type configurations, each sensor (S1

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and S2) delivers independent measurements of the same attribute or features, provides robustness and fault-tolerance. These competing sensors in this system do not necessarily have to be identical. In cooperative type of configuration, data provided by two independent sensors (S4 and S5) are used to derive information that would not be available from a single sensor.

For the proposed solution, hybrid configuration of sensors used comprising of all the three configurations. Complementary and Cooperative configurations help in extracting features from various angles of the airport environment. Competitive configuration allows data collection in different environmental conditions.

Object Detection and Classification

Object detection and classification has multiple steps such as data collection from heterogeneous sensors, extract/measure features, provide the pre-processed feature information to information fusion step and later identify and classify the object to provide the data for further stage processing by the hypothetical airport monitoring system. Fig 3 shows the steps involved in the overall processing.

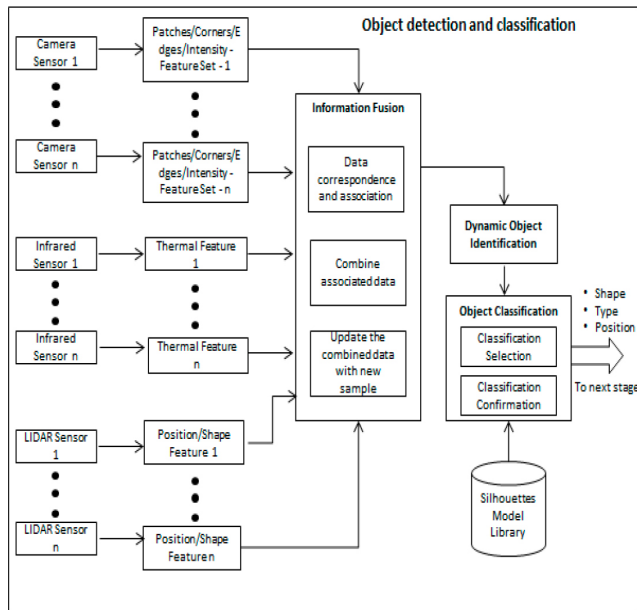


Fig 3. Architecture for Object detection and classification using data fusion and model mapping

Information Fusion

Information fusion step combines information inputs from different sources in order to get a more precise output which is generally used for decision making tasks. This step consists of three sub steps [3]: data association sub step, which finds the data correspondence between the different sources for disparity; combine associated data sub step, combines the associated data into an instantaneous data set; and update sub step, which incorporates data from new instances into the already combined information.

Several methods are followed to combine information from different sensor observations, these can generally be classified by the inference approach they are based on: Bayesian, Evidential and fuzzy, but similar approaches can be used. The fusion approaches take into

account all the available information from observed and known objects, such as kinetic information (position, velocity) and class information. The purpose of these approaches is to observe the degree of improvement achieved by the inclusion of class information. Although there are several approaches for fusing information from different sensors, few of them consider [3] the uncertainty and imprecision from sensors and integrate them into the detection.

The transferred belief model (TBM) represents, in a quantified way, beliefs obtained from belief functions. This model is able to explicitly represent uncertainty and inaccuracy. Also, it manages quantitative and qualitative data and models the unknown evidence as well as the known evidence. This model proposes an alternative to Bayesian theory and overcomes some of its limitations by being able to manage uncertainty, transfer belief measures, propose inference mechanisms [3], and to be clearly analogous to human reasoning processes. Proposed solution relies on TBM to represent object class hypotheses, perform evidence fusion information and to deal with data association problem at detection and classification steps.

Dynamic Object Identification

Dynamic environments have many static and moving objects interacting with each other. Distinguishing moving objects is an important part of this solution. Background subtraction techniques to recognize moving patches can be used for separating static and dynamic objects, but, the airport dynamic environment represents a challenge to background subtraction solutions. Detection based on visual features techniques use recognition and tracking of specific visual features that belong to moving objects. Recently, modern techniques have assembled solutions using machine learning tools to build classifiers and recognized moving or potential moving objects in a camera image. Other approaches use information from ranged sensors to build a representation of the map and highlight inconsistencies, assuming these belong to moving objects. The occupancy approach is the most used representation [3] using probabilistic grids to represent the occupancy of the map.

Object Classification

Object classification provides important information such as Shape, Size and position to object tracking stage of hypothetical system. LIDAR sensor measurements provide a good estimation of the width of the detected object; width estimation gives an idea of the class of detected object. Radar measurements provide an estimation of the relative speed of the detected object (target) which can be used to differentiate potential objects of interest, such as aircraft. Camera images are used to extract appearance features from areas of interest (image patches) and use these features to decide if this area contains an object of interest such as ground vehicles, personnel etc.

The most common approach to object classification is using data from both passive sensors such as camera and active sensors such as LIDARs. Machine learning and object classifier approaches help in storing various possible object classes belonging to airport environments and are used as model mapping in the object classification step. 3D synthetic models library [4] of models provides information for object classifier. This library contains fully textured 3D objects of airports including buildings, terminals, taxiways, runways, control tower, communication towers, aircrafts, ground vehicles, birds, UAVs, hot air balloons, paragliders etc.

In order to classify objects from camera 2D images, the most popular approach is followed using a sliding-window paradigm [3] where the detection window is tried at different positions and scales. For each window, visual features are extracted and a classifier (usually pre-trained off-line) is applied to decide if an object of interest is contained inside the window. A machine learning technique to build a classifier using the HOG descriptors is computed for each set of objects. This technique needs to have as an input a set of positive and negative examples of the object it intends to classify. In our case, the positive examples are the set of images containing an object of interest (i.e., aircraft, ground vehicles, birds etc.). The negative examples are images without the objects of interest, generally images of clutter.

The use of a 3D laser scanner as a reference sensor is used to identify scenarios where the false classification objects could be possible. This is avoided by using the three-dimensional shape of the object as a discriminating factor. A 3D representation [5] can allow the ability to have more information about the shape of the obstacles in airport environment. Moreover, a 3D segmentation process can be used to identify the moving objects of interest. Using 3D segments as Regions of Interest, a point cloud classification can be implemented to extract class information. This could allow not only to focus on the objects of interest, but in the common obstacles that usually generate false detections and false classifications.

Case Study on Data Fusion

A case study demonstrating the sensor fusion of the synthetic data is presented here using data sets from two ranging sensors in redundant configuration. Sensors are arranged in a competitive configuration. This configuration helps positional corrections, allows identifying target vehicles accurately in degraded weather conditions and obstructions in surrounded topography.

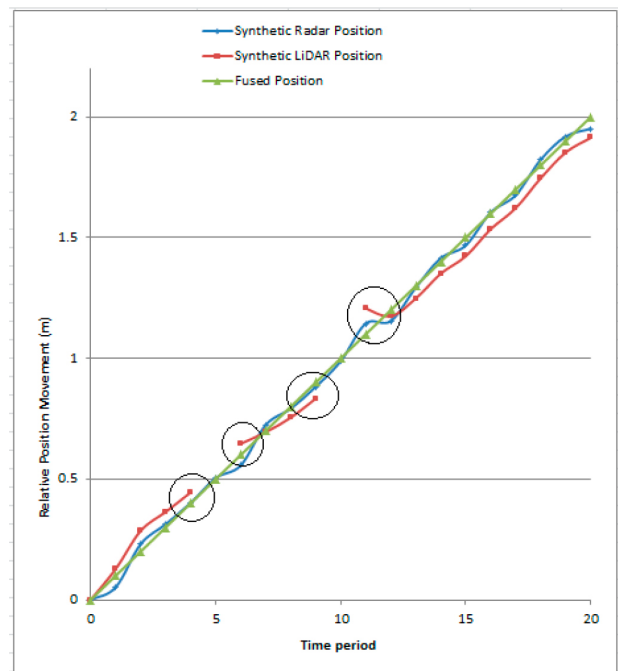


Fig 4. Longitudinal Position fusion using data from two heterogeneous sensors in redundant configuration

Redundant sensors relative position can be stabilized after correlating data from each sensor and fusion to calculate the most accurate path. This enables the system with higher availability and continuity of the position data for tracking.

Fig 4 shows the relative longitudinal position differences between Synthetic longitudinal position data sets from Radar and LIDAR, and calculated fusion path. Also, can be seen the LIDAR longitudinal position data error occurrences at two circled points due to line of sight obstruction is compensated by redundant Radar longitudinal position data.

Future Scope of the Solution

This data fusion and object identification solution has additional application scope in different environments. These concepts can be reused to develop applications such as,

- Highway traffic monitoring system
- Traffic Monitoring in Navy Ports
- Surveillance Monitoring
- Battle field simulation and war gaming
- Industrial production/assembly line monitoring
- Smart city platforms and Infrastructure

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Definitions/Abbreviations

3D - Three Dimensional

HOG - Histogram of Oriented Gradients

LIDAR - Light Detection and Ranging

TBM - Transfer Belief Model

UAV - Unmanned Autonomous Vehicle

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