UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

AVIDBOTS CORP. and AVIDBOTS USA CORP.,
Petitioners,

v.

BRAIN CORPORATION,
Patent Owner.

Case No. IPR2025-01602
U.S. Patent No. 10,274,325

Petition for *Inter Partes* Review of U.S. Patent No. 10,274,325

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U.S. Patent and Trademark Office
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PETITIONERS' EXHIBIT LIST

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1001	U.S. Patent No. 10,823,576
1002	File History for U.S. Patent No. 10,823,576 (Appl. No. 16/356,160)
1003	Declaration of Dr. Karam
1004	Edwin B. Olson, et al, Robust and Efficient Robotic Mapping, Massachusetts Institute of Technology, June 2008. ("Olson")
1005	Stachniss et al., *Springer Handbook of Robotics, Chapter 46: Simultaneous Localization and Mapping*, (Bruno Siciliano and Oussama Khatib eds., Springer 2d ed., 2016). ("Stachniss")
1006	U.S. Patent No. 9,538,892 ("Fong")
1007	U.S. Patent No. 9,020,637 ("Schnittman")
1008	Declaration of Dr. Mary Bolin
1009	Smith, Randall C., and Cheeseman, Peter. "On the representation and estimation of spatial uncertainty." The International Journal of Robotics Research 5.4 (1986): 56-68.
1010	Chatila, Raja, and Laumond, J. "Position referencing and consistent world modeling for mobile robots." Proceedings of the 1985 IEEE International Conference on Robotics and Automation. (1985): 138–45.Vol. 2. IEEE, 1985.
1011	Durrant-Whyte, Hugh, and Bailey, Tim. "Simultaneous localization and mapping: part I." IEEE robotics & Automation Magazine 13.2 (2006): 99-110.
1012	Davison, Andrew J., and Murray, David W. "Mobile robot localisation using active vision." Proceedings of the 5th European Conference on Computer Vision. Berlin, Heidelberg: Springer Berlin Heidelberg, (1998):809–825.
1013	Lu, Feng, and Milios, Evangelos. "Globally consistent range scan alignment for environment mapping." Autonomous robots 4 (1997): 333-349.

Exhibit	Description
1014	Grisetti, Giorgio, et al. "A tutorial on graph-based SLAM." IEEE Intelligent Transportation Systems Magazine 2.4 (2011): 31-43.
1015	Henry, Peter, et al. "RGB-D mapping: Using Kinect-style depth cameras for dense 3D modeling of indoor environments." The International Journal of Robotics Research 31.5 (2012): 647-663.
1016	*Springer Handbook of Robotics*, (Bruno Siciliano and Oussama Khatib eds., Springer 2d ed., 2016).
1017	Macenski, Steve, and Jambrecic, Ivona. "SLAM Toolbox: SLAM for the dynamic world." Journal of Open Source Software 6.61 (2021): 2783.
1018	Grisetti, Giorgio, Stachniss, Cyrill, and Burgard, Wolfram, *gmapping*, OpenSlam.org, https://openslam-org.github.io/gmapping.html (last visited Oct. 16, 2025).
1019	Grisetti, Giorgio, Stachniss, Cyrill, and Burgard, Wolfram. "Improving Grid-based SLAM with Rao-Blackwellized Particle Filters by Adaptive Proposals and Selective Resampling," Proceedings of the 2005 IEEE International Conference on Robotics and Automation (ICRA). (2005)2432–37.
1020	Giorgio Grisetti, Cyrill Stachniss, and Wolfram Burgard. "Improved Techniques for Grid Mapping with Rao-Blackwellized Particle Filters." IEEE Transactions on Robotics, 23.1 (2007):34-46.
1021	Tully Foote, *Community Metrics Report: July 2015*, ROS.org, http://download.ros.org/downloads/metrics/metrics-report-2015-07.pdf (last visited Oct. 16, 2025).
1022	Plaintiff Brain Corporaiton's [sic] Objections and Responses to Defendant's First set of Interrogatories (Nos. 1–9) (Redacted Excerpt)
1023	Gutmann, J-S., and Kurt Konolige. "Incremental mapping of large cyclic environments." Proceedings of the 1999 IEEE International Symposium on Computational Intelligence in Robotics and Automation. (CIRA). (1999):318–325.

Exhibit	Description
1024	Dr. Lina J. Karam, *Curriculum Vitae*.
1025	United States Patent and Trademark Office, "Classes Arranged by Art Unit," https://www.uspto.gov/sites/default/files/documents/caau.pdf (last visited Nov. 5, 2025).

TABLE OF ABBREVIATIONS

Abbreviation	Term
'807 Application	U.S. Patent Application No. 15/340,807
'325 Patent	U.S. Patent No. 10,274,325
Board	Patent Trial and Appeal Board
Challenged Claims	Claims 1–18 of U.S. Patent No. 10,274,325
Ex.	Exhibit
Fig.	Figure
IPR	*inter partes* review
Patent Office	United States Patent and Trademark Office
Petitioners or Avidbots	Avidbots Corp. and Avidbots USA Corp.
POSITA	person of ordinary skill in the art

MANDATORY NOTICES

A. Real Parties-in-Interest [37 C.F.R. § 42.8(b)(1)]

The real parties-in-interest are Petitioners Avidbots Corp. and Avidbots USA Corp. (collectively, "Petitioners" or "Avidbots"). No entity not named above is funding, controlling, or directing this Petition, or otherwise has had an opportunity to control or direct this Petition or Petitioners' participation in any resulting IPR.

B. Related Matters [37 C.F.R. § 42.8(b)(2)]

The '325 Patent that is the subject of this IPR is also the subject of a patent litigation suit brought by Patent Owner Brain Corporation entitled *Brain Corporation v. Avidbots Corporation et al.*, No. 1:24-cv-12569 (N.D. Ill.).

C. Lead and Back-Up Counsel [37 C.F.R. § 42.8(b)(3)]

Pursuant to 37 C.F.R. §§ 42.8(b)(3), 42.8(b)(4), and 42.10(a), Petitioners provide the following designation of counsel:

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A Power of Attorney accompanies this Petition in accordance with 37 C.F.R. § 42.10(b).

D. Service Information [37 C.F.R. § 42.8(b)(4)]

Service via hand delivery or postal mail may be made at the addresses of the lead and back-up counsel above. Petitioners hereby consent to electronic service, and service by electronic mail may be made at the following email address:

- GDC-AvidbotsIPR@gibsondunn.com

I. INTRODUCTION

Pursuant to 35 U.S.C. § 311, Petitioners hereby petition for IPR of U.S. Patent No. 10,274,325 (Ex1001) and seek cancellation of claims 1–18 as unpatentable under 35 U.S.C. §§ 102 and 103.

The Challenged Claims of the '325 Patent add nothing to the prior art. The patent claims systems and methods for a robot to travel within an environment and generate a map of the environment. Ex1001, Abstract, Figs. 6c, 7a, 12. However, this alleged advance is not new. Indeed, the very claim limitation that was added to independent claims 8 and 15 from independent claim 1 to obtain allowance—*i.e.*, constraining the graph between a start location and an end location, the start location and the end location being at a substantially similar location in the environment—was a standard feature ("loop closing") of robotic mapping algorithms before the time of filing. Ex1003, ¶¶38–45; Ex1004–Ex1007; Ex1009–Ex1021; Ex2023.

The Examiner's failure to recognize standard well-known features in the art at the time was in clear error. Indeed the USPTO erred from the outset by assigning the Application to a catch-all Art Unit 3664 responsible for "generic control systems" and "data processing," rather than to the specialized Art Unit 3661 responsible for "Vehicles, Navigation, and Relative Location." Accordingly, the Examiner, a member of an inappropriate Art Unit, was unfamiliar with well-known

techniques in the art and erred by failing to recognize that the limitation only captured well-known techniques in this art.

For these reasons, the Board should institute IPR to invalidate this patent that never should have issued.

II. REQUIREMENTS OF *INTER PARTES* REVIEW

A. Standing

Pursuant to 37 C.F.R. § 42.104(a), Petitioners certify that the '325 Patent is available for IPR and that Petitioners are not barred or estopped from requesting an IPR on the grounds identified herein.

B. Identification of Challenge and Relief Requested

Pursuant to 37 C.F.R. § 42.104(b), Petitioners request that the Board institute IPR of claims 1–18 of the '325 Patent under pre-AIA 35 U.S.C. §§ 102 and 103.

The '325 Patent issued from Patent Application No. 15/340,807, filed November 1, 2016. For the purposes of this Petition only, Petitioners do not challenge whether the Challenged Claims are entitled to a priority date of November 1, 2016.

The precise relief requested by Petitioners is that claims 1–18 be canceled based on the grounds below:

Ground	Claims	Basis for Rejection
1	1–18	Anticipation by Olson
2	1–18	Anticipation by Stachniss
3	1–18	Obviousness in view of Olson and Fong
4	1–18	Obviousness in view of Stachniss and Fong
5	1–18	Obviousness in view of Olson and Schnittman
6	1–18	Obviousness in view of Stachniss and Schnittman

The above challenges are made in view of the following prior art references:

1. 1. Giorgio Olson, et al, *Robust and Efficient Robotic Mapping*, Massachusetts Institute of Technology (June 2008) ("Olson") (Ex1004)

"Robust and efficient robotic mapping," a Ph.D thesis by E. B. Olson, was submitted to the Massachusetts Institute of Technology in 2008, and was publicly available no later than March 29, 2009, through MIT's digital catalog. Ex1008, ¶22. A POSITA, exercising reasonable diligence and searching for references regarding autonomous navigation and mapping would have located Olson by searching the digital catalogs of libraries, such as those at MIT or WorldCat.org. Ex1008, ¶23. For example, a skilled researcher would have located Olson by searching for keywords related to the field of invention, such as "robotic mapping," and "mobile robots." Ex1008, ¶¶24. Olson was cited 126 times from 2009 through 2015, including by authors with no apparent institutional connection to MIT, further

indicating that it was publicly available prior to the November 1, 2016, priority date of the ’325 Patent. Ex1008, ¶25. Olson therefore qualifies as prior art to the ’325 Patent under AIA 35 U.S.C. ¶ 102(a)(1). Olson was not of record during the prosecution of the ’325 Patent.

2. “Springer Handbook of Robotics (2d ed.): Simultaneous localization and mapping” (“Stachniss”) (Ex1005)

The second edition of “Springer Handbook of Robotics,” edited by Bruno Siciliano and Oussama Khatib, included Chapter 46, entitled “Simultaneous localization and mapping” (“Stachniss”), by Cyrill Stachniss, John J. Leonard and Sebastian Thrun, which was publicly available in January of 2016. Ex1008, ¶28. A POSITA, exercising reasonable diligence and searching for keywords related to the field of invention would have located Stachniss by searching the digital catalogs of libraries, such as those at Texas A&M University, the University of Nebraska at Omaha, or Harvard University, each of which hold the book containing Stachniss. Ex1008, ¶29. For example, a skilled researcher would have located Stachniss by searching for keywords like “Robotics,” “Artificial Intelligence,” or “Automation,” all of which are contained in the searchable “subject headings” field for “Springer Handbook of Robotics,” as well as “Simultaneous Localization and Mapping.” Ex1008, ¶30. Stachniss therefore qualifies as prior art to the ’325 Patent under AIA

35 U.S.C. § 102(a)(1). Stachniss was not of record during the prosecution of the '325 Patent.

3. U.S. Patent No. 9,538,892 ("Fong") (Ex1006)

U.S. Patent No. 9,538,892 ("Fong"), titled "Robot Management Systems for Determining Docking Station Pose Including Mobile Robots and Methods Using Same," was filed on October 5, 2013 and published on April 10, 2014. Fong therefore qualifies as prior art to the '325 Patent under AIA 35 U.S.C. §§ 102(a)(1), (2). Fong was not of record during prosecution of the '325 Patent.

4. U.S. Patent No. 9,020,637 ("Schnittman") (Ex1007)

U.S. Patent No. 9,020,637 ("Schnittman"), titled "Simultaneous Localization and Mapping for a Mobile Robot," was filed on March 8, 2013 and published on May 8, 2014. Schnittman therefore qualifies as prior art to the '325 Patent under AIA 35 U.S.C. §§ 102(a)(1), (2). The Patent Publication that later issued as Schnittman was cited during prosecution, but was not substantively addressed by the Examiner. Ex1002, 205, 244.

C. How the Challenged Claims Are To Be Construed Under 37 C.F.R. § 42.104(b)(3)

A claim subject to IPR shall be construed using the same standard as in a civil action. 37 C.F.R. § 42.100(b). The Board need only construe terms "to the extent

necessary to resolve the controversy." *Nidec Motor Corp. v. Zhongshan Broad Ocean Motor Co.*, 868 F.3d 1013, 1017 (Fed. Cir. 2017). Petitioners submit that no construction of any claim term is necessary for the Board to resolve, and that the Challenged Claims would have been anticipated and/or obvious under any reasonable construction.

D. How the Challenged Claims Are Unpatentable Under 37 C.F.R. § 42.104(b)(4)

An explanation of how the Challenged Claims are unpatentable under the statutory grounds identified above, including the identification of where each element of the claim is found in the prior art patents or printed publications, is provided below.

E. Supporting Evidence Under 37 C.F.R. § 42.104(b)(5)

The exhibit numbers of the supporting evidence relied upon and the relevance of the evidence to the Challenged Claims, including an identification of specific portions of the evidence that support the challenge, are provided below. A list of exhibits with the exhibit number and a brief description of each exhibit is also included in this Petition pursuant to 37 C.F.R. § 42.63(e). The technical information and grounds for rejection explained in this Petition are further supported by the Declaration of Dr. Karam, Ph.D. (Ex1003).

F. Payment of Fees

Pursuant to 37 C.F.R. §§ 42.103 and 42.15(a), the required fee is being submitted herewith. The Office is authorized to charge any fee deficiency, or credit overpayment, to deposit account no. 50-1408, including additional fees due in connection with this Petition.

III. TECHNICAL BACKGROUND

A. Alleged Invention of the '325 Patent

The '325 Patent purports to provide a robot having an allegedly improved mapping capability. Ex1001, Abstract. Specifically, the '325 Patent discloses a robot that: (1) generates a map of the environment from a graph of nodes, wherein sensor data from the robot is associated with each node (Figure 6A, below); (2) performs "scan matching" between sensor data taken from different nodes to create extended scan groups (Figure 7B, below); and (3) constrains the graph to start and end at a similar location (Figure 6C, below). Ex1001, Abstract.

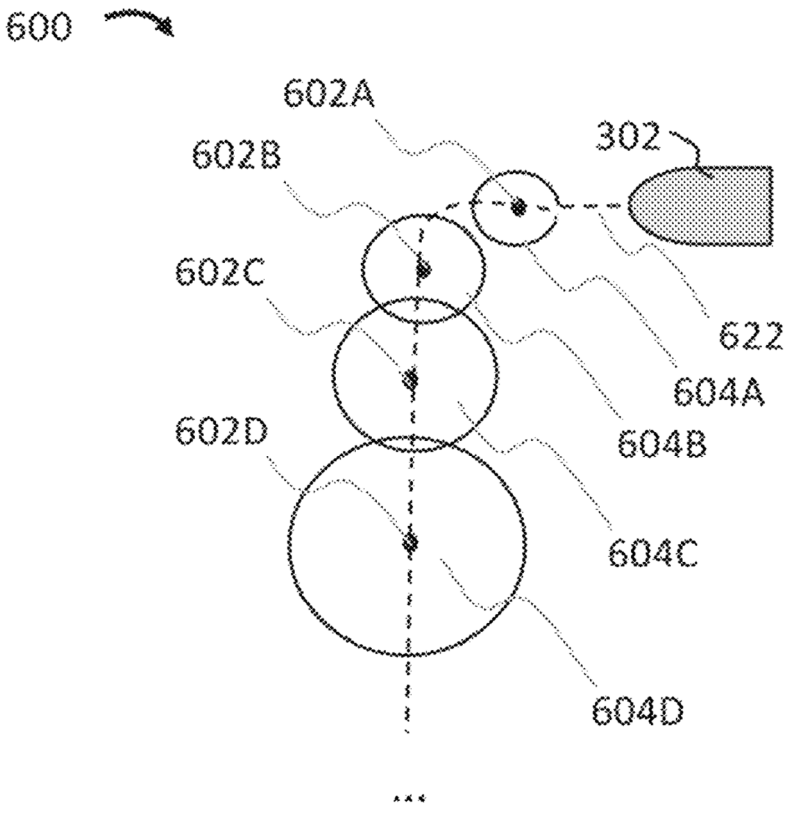


FIG. 6A

Ex1001, Fig. 6A.

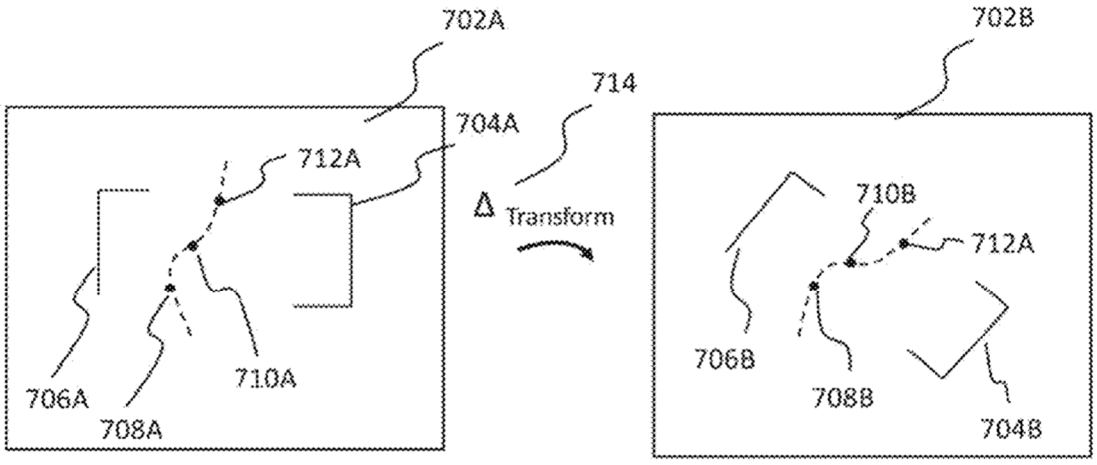


FIG. 7B

Ex1001, Fig. 7B.

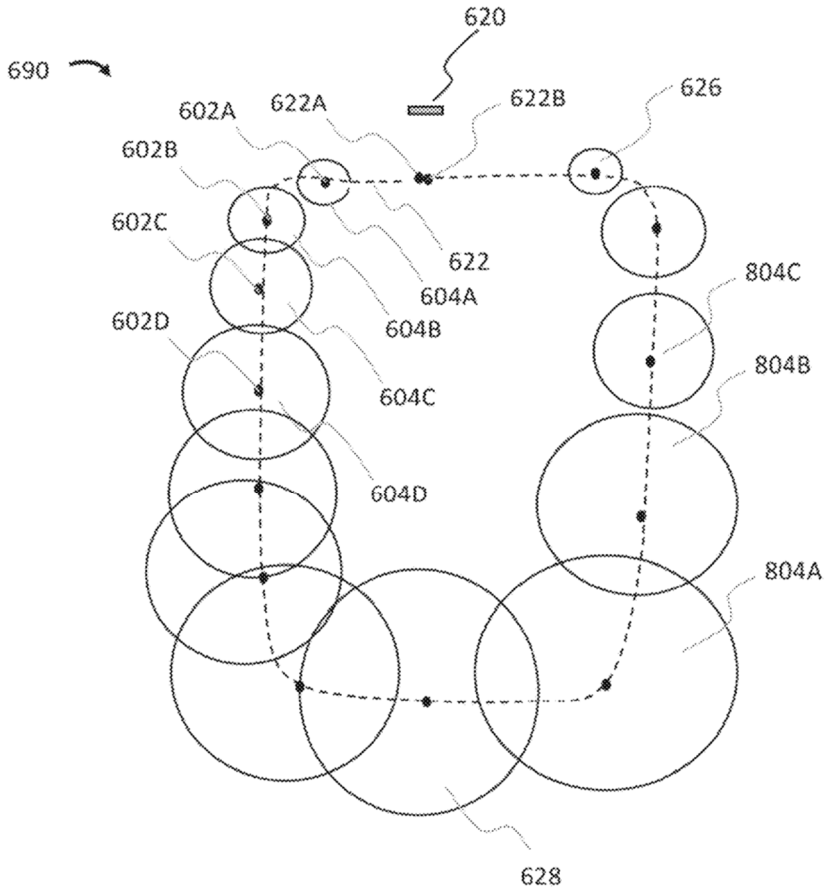


FIG. 6C

Ex1001, Fig. 6C.

B. Prosecution History of the ’325 Patent

The ’325 Patent was issued from the ’807 Application, filed November 1, 2016. The ’807 Application was reviewed by Art Unit 3664, responsible for Class 700, “Data Processing: Generic Control Systems or Specific Applications.” *See* Ex1002, 212; Ex1025.

During prosecution and prior to allowance, the Applicant amended the claims once. Ex1002, 268–76. In an Office Action dated May 31, 2018, the Examiner issued a Non-Final Rejection, wherein he: indicated that claims 1–7 were allowable; rejected claims 8, 10, 13–16 and 18 as anticipated by U.S. Patent Publ. No. 2012/0121161 ("Eade"); and objected to claims 9, 11, 17, and 19–20 as being dependent upon rejected independent claims 8 and 16. Ex1002, 212–16.

In response, on August 28, 2018, the Applicant removed certain limitations from claim 1, which were then added to dependent claim 2, and revised other limitations of claim 1. Ex1002, 269–70. Further, the revised limitation of claim 1 related to "constraining the graph" was added to independent claims 8 and 16. Ex1002, 271–72.

The Examiner allowed the claims on December 18, 2018 (Ex1002, 280), and the '325 Patent issued on April 30, 2019. Because more than nine months have passed since issuance, the '325 Patent is eligible for IPR. 35 U.S.C. § 311(c)(1).

C. Person of Ordinary Skill in the Art

The '325 Patent relates to the field of robotic mapping and navigation. Ex1001, 1:25–27. A person of ordinary skill in the art at the time of the earliest effective filing date of the '325 Patent would have had a Bachelor's degree or higher in electrical or mechanical engineering, or computer science (or equivalent) and at

least two years' experience in research, design and/or development of autonomous robotics and/or robotic mapping/navigation and/or a related field. Additional education could substitute for experience, and vice versa. Ex1003, ¶25.

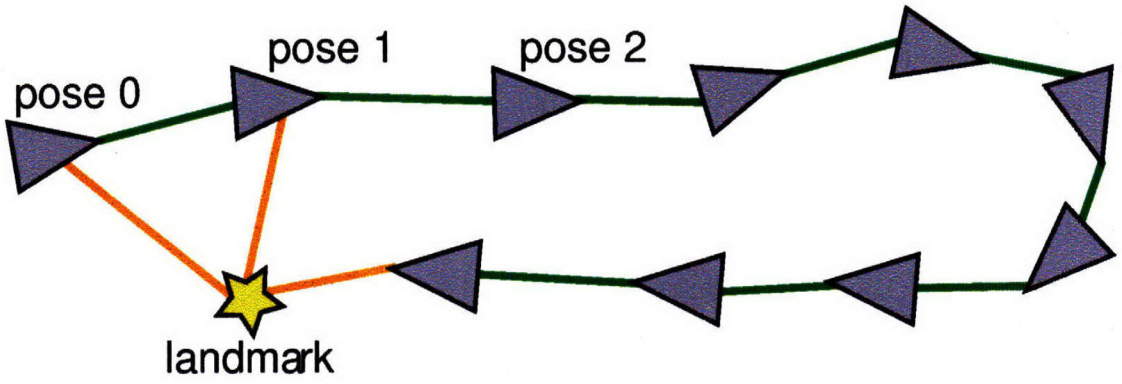
IV. GROUNDS OF UNPATENTABILITY

A. Ground 1: Anticipation by Olson

As explained below and in further detail in the Declaration of Dr. Karam, Olson discloses all elements of claims 1–18 of the '325 Patent.

1. Overview of Ground and Prior Art

Olson discloses an optimization algorithm technique for robots to construct a map based on large quantities of noisy sensor data and a robot implementing that method. Ex1004, 3. Just like the '325 patent, Olson discloses a robot that generates a map of an environment from a graph of nodes based on sensor data associated with each node. For example, in Figure 4-1 (below), Olson shows a robot that has navigated through several poses (*i.e.*, nodes), and has observed the same landmark from three of those positions. As a result, each pose is relationally connected to the poses immediately prior and subsequent to it, as in a graph, and the nodes that observed the landmark are additionally connected to that landmark.



Ex1004, Fig 1-4.

Olson, like the '325 patent also describes the use of extended scan groups. It explains that it identifies "poses that might contain overlapping sensor readings," first using odometry measurements and sensor properties to establish a prior likelihood of inclusion, and then calculating the posterior probability of overlap based on landmark and/or laser matching, depending on the sensor. Ex1004, 33–37.

Olson further discloses both "batch and online versions of [its] algorithm." Ex1004, 3. Olson maintains an error estimate for each node. Ex1004, 22–26, 65–68. In the online version, the algorithm optimizes the graph each time the robot adds a node. Ex1004, 89–103. The robot uses the optimized graph with its sensor measurements to create a representation of the environment, as depicted in Figure 5-4, reproduced below.

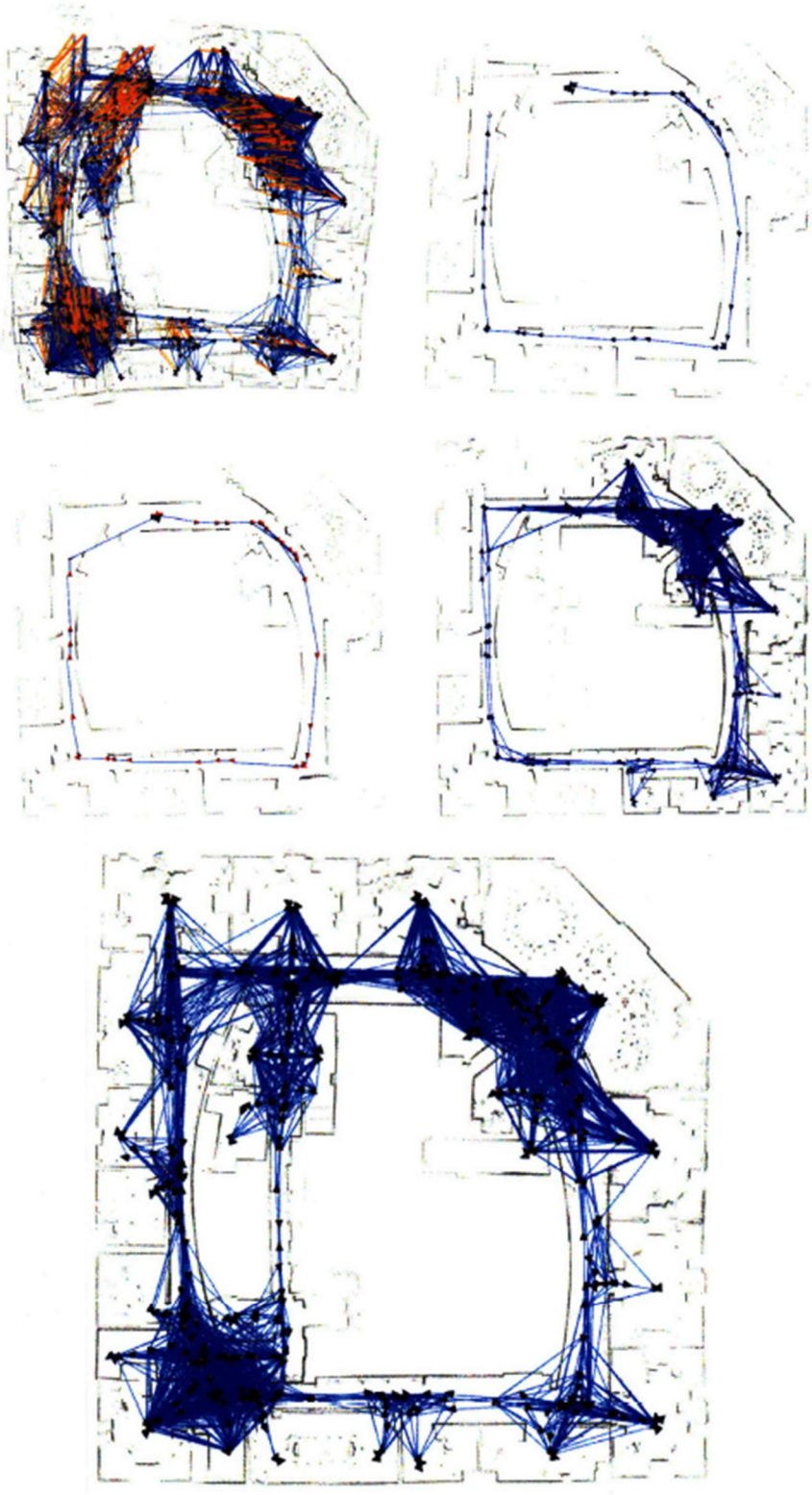


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

Further, Olson, like the '325 patent, discloses constraining the graph between a start and end position wherein the start and end position are substantially similar. Olson explains that this is known in the prior art as "loop closing." Ex1004, 13. Olson further explains that loop-closing "can be used to refine the estimate of the robot's trajectory." It depicts loop closing in Figure 4-1 (below).

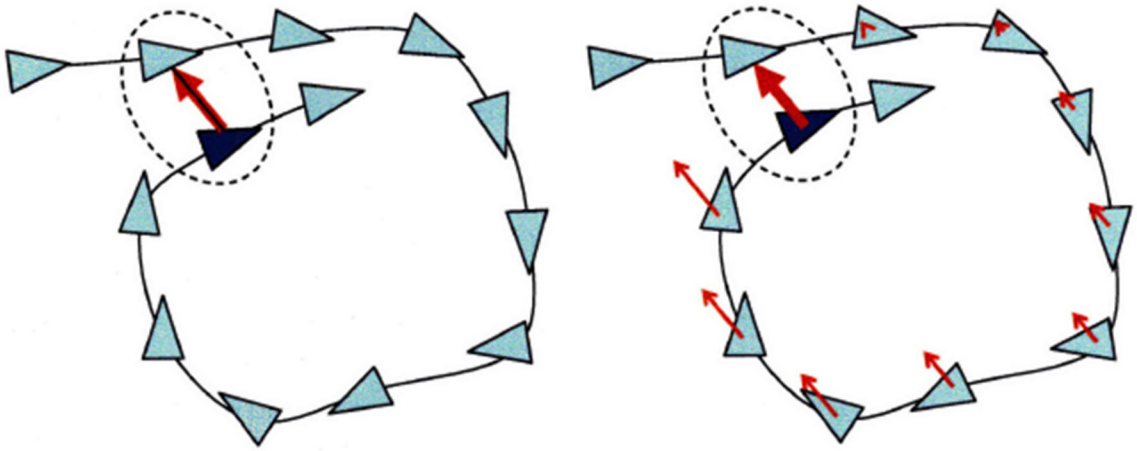


Figure 4-1: Map Optimization Intuition. The χ^2 error of a graph with a poorly-satisfied constraint (left, red arrow) can be reduced by distributing small adjustments around the nodes in the loop (right).

Ex1004, Figure 4-1.

2. Detailed Analysis of Ground 1

a. Element 1[pre]

"A method of generating a map by a robot, comprising:"

To the extent the preamble is limiting, Olson discloses it. Ex1003, ¶¶80–86. Olson discloses a method that allows a robot to simultaneously traverse and map an area based on robot movement and sensor measurements. Ex1004, 3, 9–17, 43–49, 89, 97, 105–06, 109–10, 113–14; Ex1003, ¶¶80–86. Olson depicts several such robots, including in Figures A-1 and A-5 (below).

Figure A-1: Talos. Our vision test-bed was MIT's DARPA Grand Challenge vehicle. The vehicle has five cameras (two forward, left, right, rear), and a high-quality IMU/GPS system for both dead-reckoning and ground-truthing.

Ex1004, Figure A-1.

Figure A-5: SICK Laser Scanner on a small indoor robot.

Ex1004, Figure A-5.

Olson discloses several maps produced by its method, including a map of the Intel Research Center, depicted in Figure 3-17 (below). *See also* Ex1004, 49 (describing the IRC dataset), 43–53 (describing other generated maps).

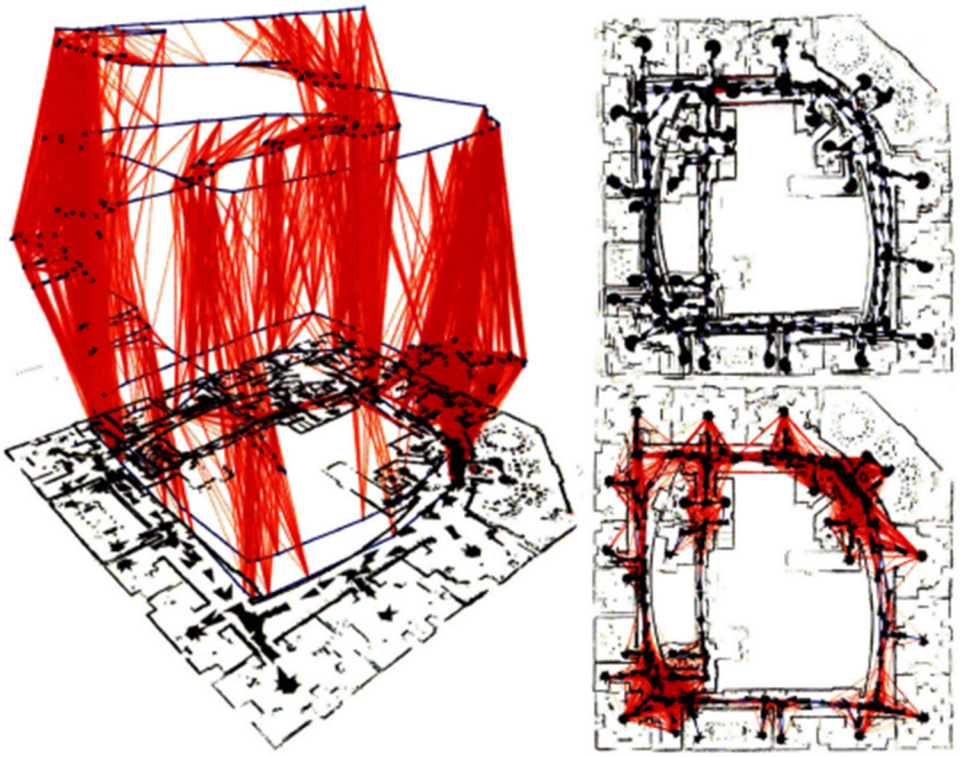


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

b. Element 1[a]

"traveling, by the robot, in an environment;"

Olson discloses this limitation. Ex1003, ¶¶87–91. For example, Olson discloses a system to allow a robot to navigate around a new or unknown environment. Ex1004, 3, 8-12, 43–49, 97, 105-106, 109, 113-114; Ex1003, ¶88. As a further example, Olson explains that it generates a map based on a graph comprising poses and edges, which represent and store information related to the robot's positions and sensor measurements as it travels through the area. Ex1004,

15; Ex1003, ¶89. As a further example, Olson explains that it presents a mapping algorithm that "encodes the *motions* of the robot as it moves from pose to pose." Ex1004, 60 (emphasis in original). As a further example, Olson explains that, in another embodiment, "[w]hen the robot travels to a new location, a new pose and a new constraint connecting that pose to the graph are created." Ex1004, 97. *See also* Ex1004, 9, 13, 19, 30, 115.

c. Element 1[b]

"generating a graph comprising a plurality of nodes, a respective node of the plurality of nodes corresponds to a scan generated by a sensor of the robot at a location in the environment;"

Olson discloses this limitation. Ex1003, ¶¶92–101. Olson discloses that "sensors are mounted on the robot." Ex1004, 12. The sensors collect data like the robot's position and the noise in the environment. Ex1004, 12. The data is collected by the sensors continuously as the robot moves through its environment. Ex1004, 11–12, 109–10, 113–14; *see also* §§ IV.A.2.a–b. These sensors can include cameras, laser scans, wireless radio frequencies, radars, lidars, inertial measurement unit, and global position systems. Ex1004, 14, 16, 23, 32, 34. The robot uses sensor measurements to build a map while traversing the environment. Ex1004, 3, 8-12, 43–49, 89, 97, 105-106, 109, 113-114.

Olson further explains that "[s]ensors observe the environment ***relative to the robot's current position***." Ex1004, 12. The robot's position (location) and sensor measurements (scan) are collected into poses (nodes), and poses are connected by edges based on the robot's movement. Ex1004, 15; Ex1003, ¶¶93–98. When a sensor detects a landmark, the robot estimates the position of the landmark, creates a node based on the landmark's estimated position, and adds an edge from the landmark node to the node from which the landmark is detected. Ex1004, 15. These nodes are collected into a "Pose/Feature graph," as depicted in Figure 1-4 (below). Ex1004, 15; *see also* Ex1004, 19–24, Fig. 2-1 (further explaining the Pose/Feature Graph). "A graph consisting of only poses and edges between poses is simply a 'pose' graph." Ex1004, 15. The graph, in turn, is used to generate a map corresponding to a representation of the environment. Ex1004, 11–17, 43–53, Figure 3-17.

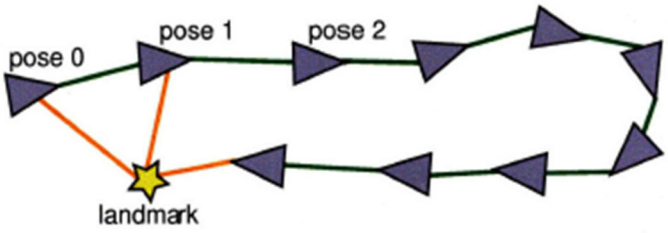


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry (green) and a landmark detector (orange).

Ex1004, Figure 1-4.

d. Element 1[c]

"performing scan matching on extended scan groups, the extended scan groups being determined in-part on at least two or more nodes of the plurality of nodes; and"

Olson discloses this limitation. Ex1003, ¶¶102–10. Olson explains that "[s]can matching is the process of finding a rigid-body transformation that improves the alignment of two scans." Ex1004, 116–17, 119–20. Olson explains that scan-matching may be accomplished using feature extraction algorithms, like SIFT, in conjunction with algorithms like RANSAC, to find the most likely rigid-body transformation based on the scan data. Ex1004, 109–113, Figure 1-3 (below), Figure 3-8, Figure 3-9; Ex1003, ¶104.

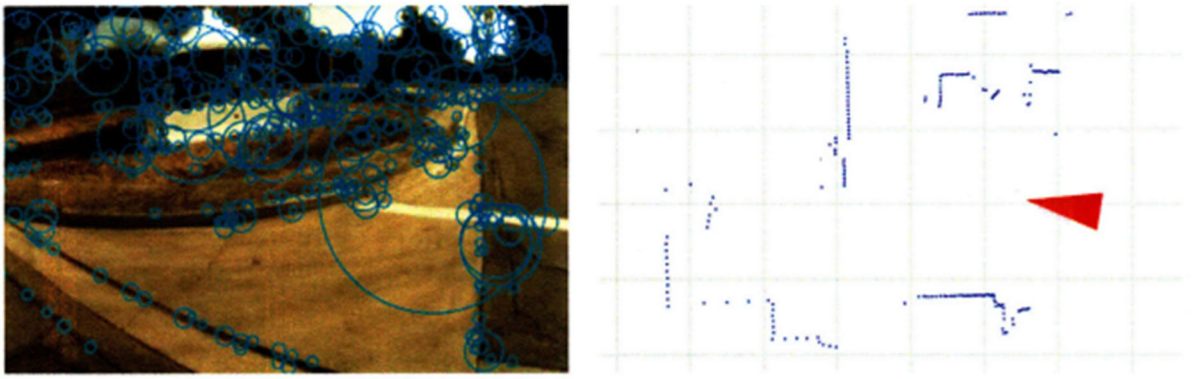


Figure 1-3: Sample sensor data. Different sensor modalities present different challenges when trying to "close the loop". Left: Camera-derived visual features can be richly descriptive, but are also cluttered and not consistently repeatable under changing lighting and viewpoint. Right: Laser-scan data from an indoor environment is composed principally of walls at 90 degree angles. While the scan is very precise, many indoor environments produce similar looking scans.

Ex1004, Figure 1-3.

Olson further explains that scan-matching may be performed using data from lidar sensors by first extracting contours, including contour endpoints, then maintaining a data structure (here, a "MinHeap") containing candidate contour merges. Ex1004, 116–17. Olson further discloses an algorithm that iteratively selects the most-probable merge, until all contour endpoints had been merged. Ex1004, 117–120, Figures A-9 and A-10 (below); Ex1003, ¶105.

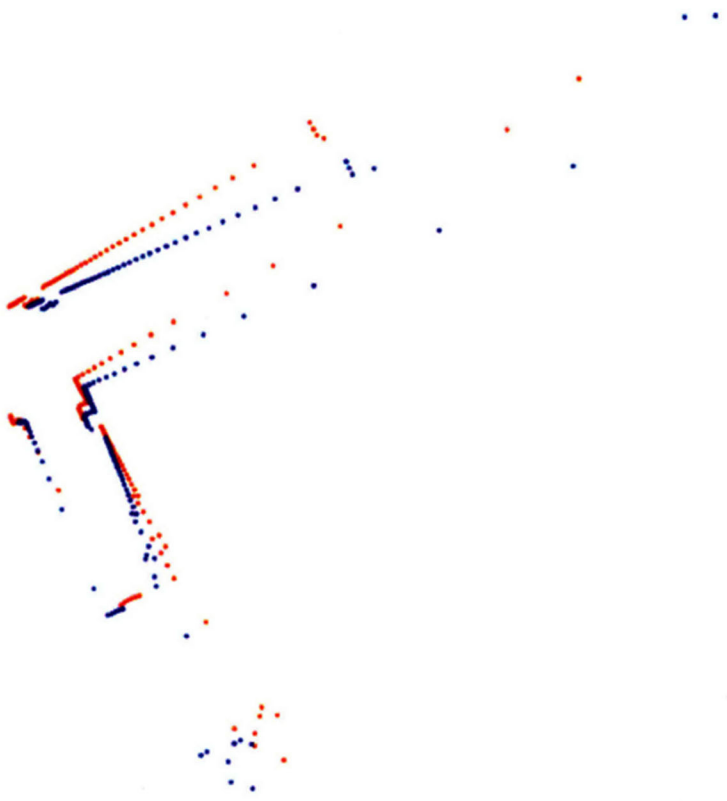


Figure A-9: Scan Matching. Two scans taken 133 ms apart are poorly aligned. Scan-matching is the process of finding a rigid-body transformation that improves the alignment of two scans. This alignment corresponds to the motion of the robot.

Ex1004, Figure A-9.

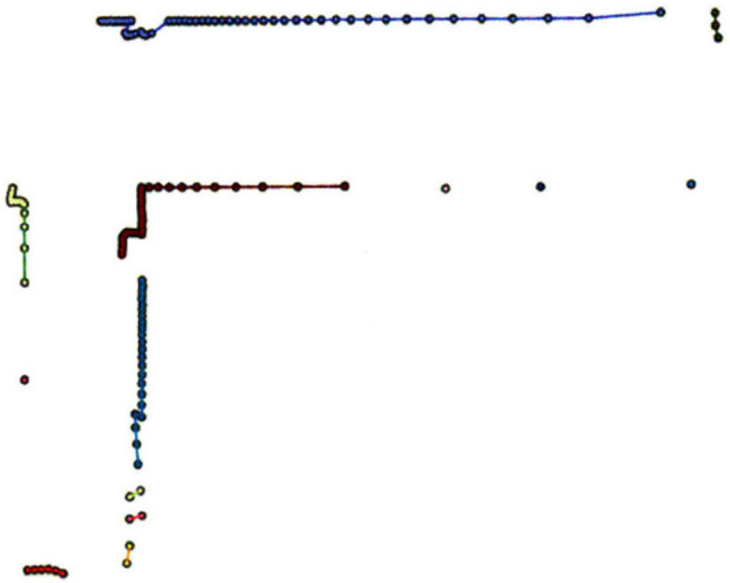


Figure A-10: Contour Extraction. A laser scanner measures only a discrete set of points; it is necessary to infer the *contours* of the surface being sampled as shown here.

Ex1004, Figure A-10.

Olson further discloses the use of extended scan groups. Ex1003, ¶¶106–109. For example, Olson discloses that is uses scan-matching on "temporally consecutive scans," corresponding to the claimed extended scan group. Ex1004, 116–17; *see also* Ex1004, 46, 116–17, 119–20; Ex1003, ¶106. Olson further discloses that its algorithm performs "data association" (scan matching) "on groups of observations at once" (extended scan groups). Ex1004, 30; Ex1003, ¶107. Olson further discloses that such groups are not limited to consecutive scans, and may comprise all pose-nodes wherein the mapping algorithm determines that the pose is within

detection range of a landmark, so that each of those nodes comprises an extended scan group. Ex1004, 33–34; Ex1003, ¶¶108–09. Olson provides an example of the above functionality with respect to loop closing, explaining that it may use an initial estimate of the position to "estimate the probability that those two positions are close enough together for them to have observed the same [overlapping] environmental features," in which case the algorithm performs scan-matching between those poses such that a successful scan-match closes a loop within the graph, corresponding to an extended scan group. Ex1004, 32; Ex1003, ¶¶108–09.

e. Element 1[d]

"constraining the graph between a start location and an end location, the start location and the end location being at a substantially similar location in the environment."

Olson discloses this limitation. Ex1003, ¶¶111–15. Olson discloses that its system performs loop closures, where the robot "recognize[s] that it is at its starting position" (start location and end location being at a substantially similar location in the environment), which helps create better maps because it creates a "geometric relationship [constraint] between the first and last position of the robot." Ex1004, 13–14. Olson further explains that a loop closure creates a "topological" and "metrical relationship" (constraining) between the start point and the end point

which can be used to reduce error and uncertainty along the route. Ex1004, 13–14; Ex1003, ¶113. These relationships are used to further constrain pose locations during graph optimization, limiting the uncertainty of the estimated position of each pose within the loop. Ex1003, ¶113; Ex1004, 13–14, 94, 97–98. 101–03. Olson depicts a simple loop closure in Figure 4-1 (below), and explains that loop closure reduces the overall chi-squared error. Ex1004, 60.

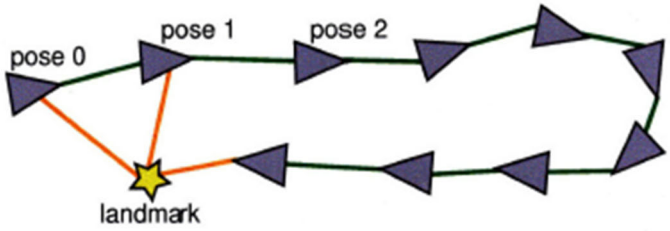


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry (green) and a landmark detector (orange).

Ex1004, Figure 4-1.

Olson depicts a map of the IRC created using its loop-closure algorithm in Figure 5-4 (below).

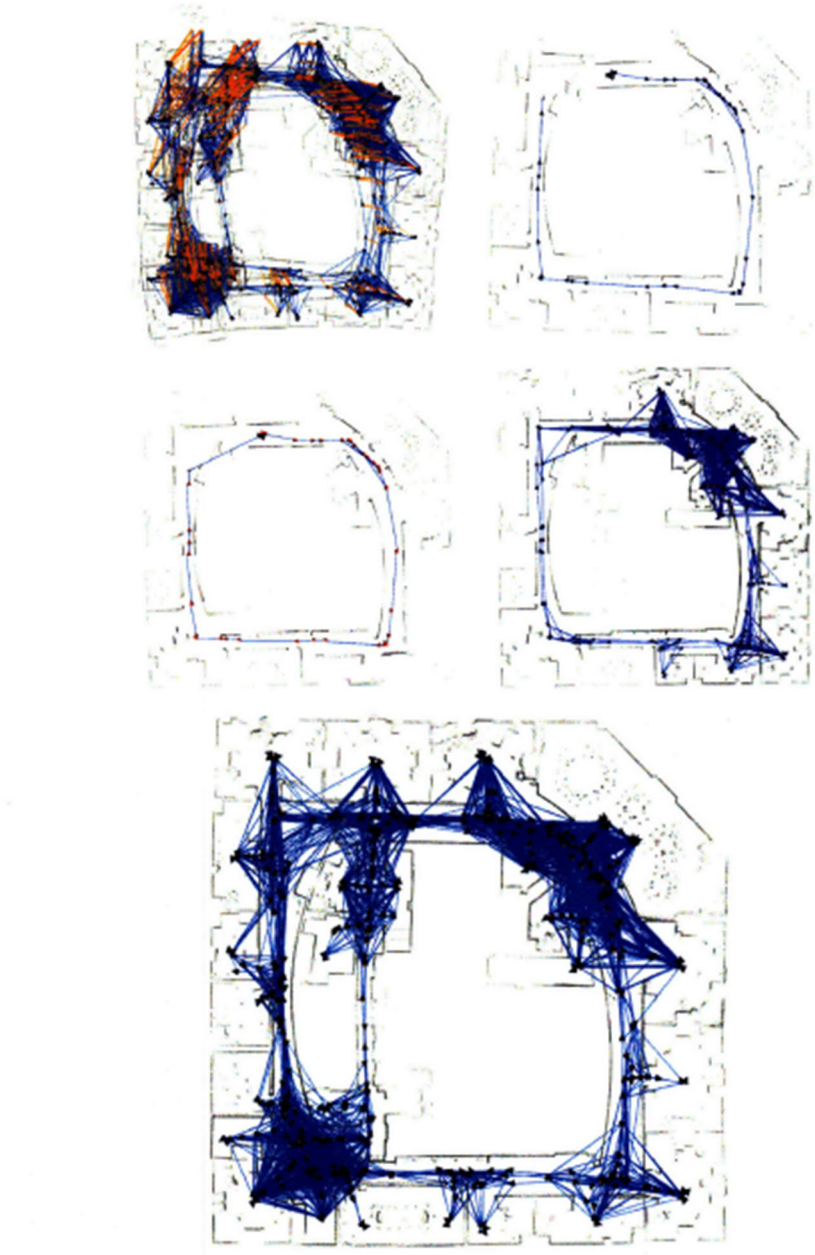


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

f. Element 2[a]

"The method of claim 1, further comprising: associating a range of possible locations in the environment with the respective one of the plurality of nodes based at least in-part on the scan matching;"

Olson discloses this limitation. Ex1003, ¶¶116–24.

Olson discloses that each node in the graph comprises a range of possible locations based on the uncertainty associated with the pose. Ex1003, ¶¶117–19. For example, Olson explains that its algorithm addresses map building, and it explains that "[i]n general terms, the map building problem can be described as finding the posterior probability distribution function of a map *x*." Ex1004, 12. Olson further discloses that "[t]he nodes of a pose/feature graph are the same as the random variables of a graphical model." Ex1004, 20; see also Ex1004, 12–13, 19, 22. Olson further discloses that the probability distribution for a node may be represented as a range that "resemble[s] radially-oriented ellipses." Ex1004, 118; see also Ex1004, 13, 22, 32. Olson further discloses that confidence and error may be modeled as an information matrix, Σ^{-1}, and with a chi-squared error matrix, where chi-squared represents a range of uncertainty. Ex1004, 19–25, 32, 63–66, 118. A POSITA would have understood that these disclose a range associated with each node based on a confidence measure. Ex1003, ¶¶117–19.

Additionally, Olson's disclosures are within the '325 Patent's description of "range," which variously explains that the range may be computed according to "a posterior probability distribution," "the mean computed position plus the covariance," or "using other statistical methods, such as the cross-variance, variance, chi-square distribution, and/or any other statistical methods used in, for example, Simultaneous Localization and Mapping ('SLAM') and/or other techniques for determining pose known in the art." Ex1001, 16:26–42; Ex1003, ¶119.

Olson further discloses that this range is based at least in-part on scan matching, which contributes to the uncertainty of the pose. Ex1003, ¶¶120–23. As explained in IV.A.2.d, Olson discloses a method of estimating the distance traveled by the robot and closing loops by using scan matching. Ex1003, 30–34, 46. Olson further discloses that its scan-matching algorithm first identifies "a number of naïve matches ('hypotheses')" for representing possible locations of the second node in relation to the first, and then "comput[es] the subset of hypotheses that is most self-consistent" to determine the likely true location, as depicted in Figure 3-5 (below). Ex1004, 31, 37–43. Olson explains that it does so using a "variant of Dijkstra's Algorithm," which computes the "***relative positional uncertainty*** between nodes a and b." Ex1004, 32.

g. Element 2[b]

"determining confidences associated with a respective one of the range of possible locations;"

Olson discloses this limitation. Ex1003, ¶¶125–30. As explained in IV.A.2.f with respect to element 2[a], Olson discloses that each node in the graph comprises a range of possible locations based on the uncertainty associated with the pose. Ex1003, ¶125. For example, Olson explains that it "find[s] the posterior probability distribution function of a map x," which may be represented as a range that "resemble[s] radially-oriented ellipses." Ex1004, 12, 118; *see also* Ex1004, 12–13, 19, 22, 32. Olson further discloses that "confidence is the inverse of the covariance matrix," Σ_i^{-1}. Ex1004, 23. Olson also discloses that it tracks "the confidence of each individual node." Ex1004, 72.

The '325 Patent variously explains that "[t]he confidence can be based at least in part on the ranges," Ex1001, 21:1–2, "[t]he confidence can be represented as a covariance matrix," Ex1001, 21:38–39, and "confidence can also be represented with other statistical indicia known in the art, such as variances, sample variances, correlations, etc.," Ex1001, 21:44–47. A POSITA would have understood that Olson's disclosures disclose the ranges and confidences described and claimed in the '325 Patent. Ex1003, ¶129.

h. Element 2[c]

"optimizing the graph to find a location of the plurality of nodes based at least in-part on the confidences; and"

Olson discloses this limitation. Ex1003, ¶¶131–35. For example, Olson discloses that its algorithm addresses map building, and it explains that "[i]n general terms, the map building problem can be described as finding the posterior probability distribution function of a map *x*." Ex1004, 12. Olson explains that it optimizes the graph using a hybrid method combining stochastic gradient descent and least-squares. Ex1004, 61–72. Olson depicts this in Algorithm 7 (below). Ex1004, 71–72.

Algorithm 7 SGD-Optimize-Graph

```
1: λ = 1/3
2: repeat                                   Optimize the graph
3:    Randomly permute order of Constraints
4:    {Update approximation M = J^T Σ^-1 J. Let M_i be the i^th diagonal block.}
5:    for all {a, b, t_ab, Σ_ab} in Constraints do
6:       compute R using Eqn. 4.15
7:       W = R^T Σ_ab^-1 R                  Correction based on the
8:       for all i ∈ [a + 1, b] do          Confidences of the
9:          M_i = M_i + W                   plurality of nodes
10:         Update error-distribution trees with M
11:      end for
12:   end for
13:   Γ = max(Σ_i^-1)
14:
15:   {Modified Stochastic Gradient Descent}
16:   for all {a, b, t_ab, Σ_ab} in Constraints do
17:      r = X_a^-1 ⊕ X_b
18:      r(3) = mod2pi(r(3))
19:      compute R using Eqn. 4.15
20:      s = -(b - a)λR^T Γ^-1 Σ_ab^-1 r    Correction based on the
21:      s_max = X_b - (X_a ⊕ T_ab)         Confidences of the
22:      s = clamp(s, s_max)                plurality of nodes
23:      distribute(a + 1, b, s)
24:   end for
25:   λ = λ/(λ + 1)
26: until converged
```

Ex1004, Algorithm 7 (annotated).

Olson further explains that it optimizes the map to find a location of the plurality of nodes. Ex1004, 16; Ex1003, ¶132. For example, in Figure 4-14 (below), Olson depicts the initial configuration of the nodes and the environment in

comparison to the optimized configuration for data produced in the Intel Research Center (IRC), depicted in Figure 3-17 (below). Ex1004, 83–84.

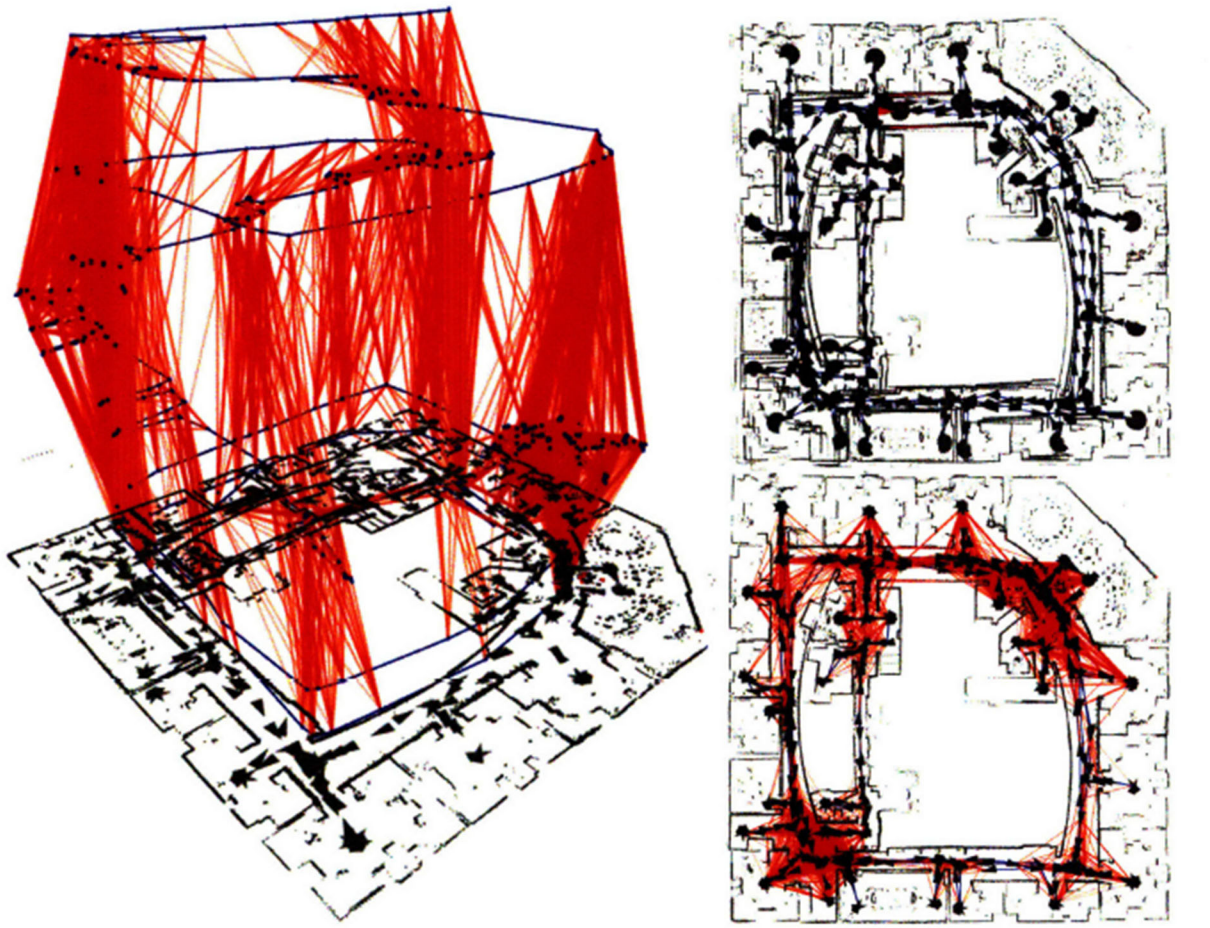


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

Olson further explains that its optimization is based on the confidences. Ex1003, ¶133. For example, Olson explains that its hybrid optimization algorithm minimizes the total error (*i.e.*, maximize the confidence) of the graph. Ex1004, 63–

66; Ex1003, ¶134. Olson further discloses that "the goal [of the graph optimization] is to estimate the positions of all the nodes (the state variables)" and "[t]hat a reasonable goal for an optimization is to ***reduce*** χ^2 error." Ex1004, 16, 94. Olson explains that it reduces error by calculating "a value *d* represent[ing] a change in the state variable that will ***minimize*** the χ^2 error." Ex1004, 24, 63–66.

i. Element 2[d]

"generating the map from the optimized graph, the generation of the map comprises ray tracing with the scans generated by the sensor, the scans being associated with the plurality of nodes."

Olson discloses this limitation. Ex1003, ¶¶136–42. As explained in IV.A.2.h, Olson discloses generating a map from the optimized graph. And as explained in IV.A.2.c, sensor scans are associated with the plurality of nodes. Olson further discloses that generation of the map comprises ray tracing using the scans associated with the plurality of nodes. Ex1004, 34–36, 107, 110–12; Ex1003, ¶¶138–41. For example, Olson discloses that it uses SIFT feature extraction, and that "[e]ach bearing to the feature corresponds to a ray: when the rays from different observations intersect [ray-tracing], we can estimate the location of the feature [a step in generating the map]." Ex1004, 34, 110–112; Ex1003, ¶138. Olson depicts localization of landmarks through ray-tracing in Figure A-3 (below).

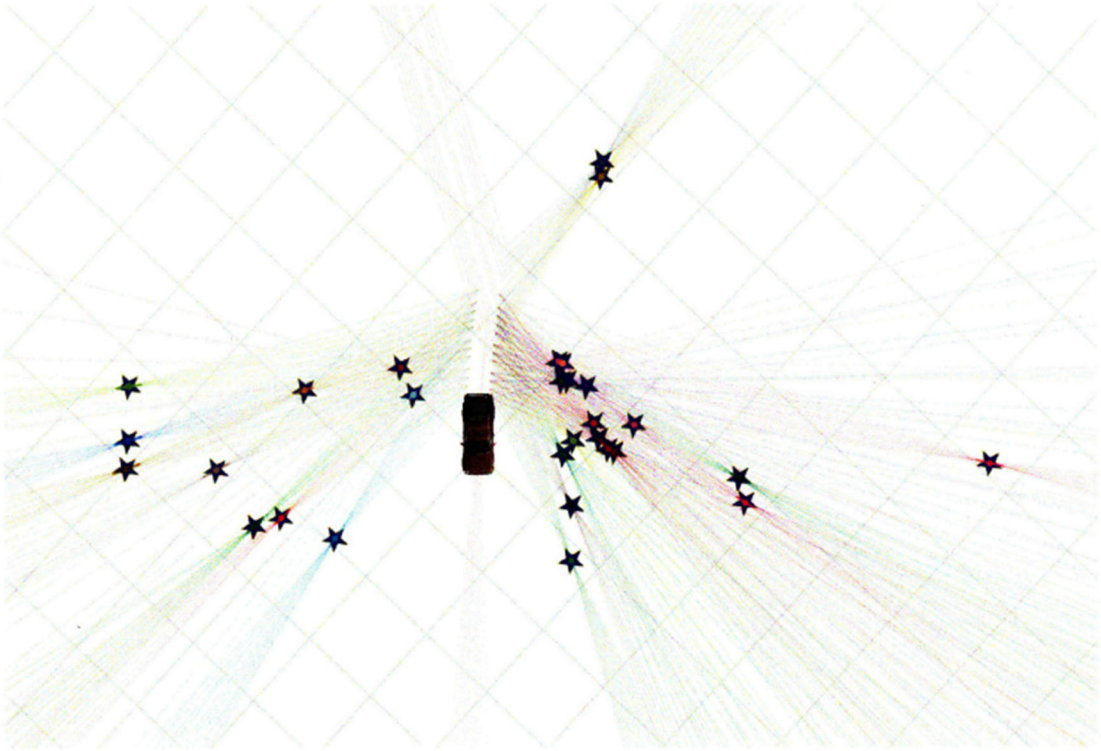


Figure A-3: SIFT Landmark Initialization. Landmarks are computed by tracking SIFT features over short motions of the robot: when the intersection of the bearings converges near a single point, a landmark is initialized.

Ex1004, Figure A-3.

Olson further discloses use of rays with respect to laser scanners. Ex1004, 117–19; Ex1003, ¶140. For example, Olson explains that "[l]aser scanners are strictly line-of-sight, and are susceptible to occlusions." Ex1004, 118. Accordingly, "better scan matching results can be obtained by building the cost lookup table using *several* previous scans." Ex1004, 118. A POSITA would have understood that

aligning features detected using laser-scanners in a manner which accounts for partial occlusions comprises ray-tracing. Ex1003, ¶141.

j. Element 3[a]

"The method of claim 2, wherein the optimizing of the graph, comprises: generating a cost function based at least in-part on: (1) relative locations of each of the plurality of nodes, and (2) the confidences associated with each of the plurality of nodes; and"

Olson discloses this limitation. Ex1003, ¶¶142–149. As explained in IV.A.2.h, Olson discloses optimizing the graph to find a location of the plurality of nodes based at least in-part on the confidences. Further, Olson discloses that the goal of its "optimization algorithm is to reduce χ^2 error," i.e., a cost function, based on the relative location of the nodes and the confidence associated with each node. Ex1004, 16, 94; Ex1003, ¶¶144–47. Olson discloses that its optimization algorithm proceeds by calculating a cost function on the relative locations and confidences associated with each of the plurality of nodes, and by iteratively calculating a change in the "state variable" (relative locations of each of the plurality of nodes), *d*, "that will minimize the χ^2 error" (cost function), and depicts its equation for its *d* (below). Ex1004, 63–68; *see also* Ex1004, 60; Ex1003, ¶147. As shown below, the calculation of *d* includes Σ^{-1}, which is a measure of the confidences associated with each of the plurality of nodes.

Nonlinear Least Squares	Stochastic Gradient Descent	Hybrid
$d_i = (J^T\Sigma^{-1}J)^{-1}J_i^T\Sigma_i^{-1}r_i$	$d_i = 2\lambda J_i^T\Sigma_i^{-1}r_i$	$d_i = \lambda M^{-1}J_i^T\Sigma_i^{-1}r_i$

Olson further specifically states that "[f]or each rigid-body transformation, a cost function is computed that indicates the quality of alignment [relative locations of each of the plurality of nodes]. An optimization algorithm then attempts to find the minimum-cost [confidences associated with each of the plurality of nodes] alignment." Ex1004, 116; Ex1004, 61–63; Ex1003, ¶¶146. This optimization algorithm is described in additional detail in IV.A.2.h.

k. Element 3[b]

"solving the cost function for a minimum value."

Olson discloses this limitation. Ex1003, ¶¶150–56. For example, Olson discloses that its "map optimization step, [which] makes the map 'line up'" involves "find[ing] the maximum likelihood (minimum cost [value]) position of each node." Ex1004, 16, 22–24, 55; Ex1003, ¶152. With respect to maps based on laser scans, Olson discloses that "a cost function is computed that indicates the quality of the alignment," and the "optimization algorithm then attempts to find the ***minimum-cost*** alignment." Ex1004, 116. With respect to maps based on scan-matching (*e.g.*, with camera images), Olson discloses that it "compute[s] the cost-function . . . [and] output[s] the rigid-body transformation with minimum cost." Ex1004, 119. Olson

provides the details of how it finds a graph which provides the minimum cost of its cost function in batch mode (Ex1004, 55–88), and as an incremental real-time optimization procedure (Ex1004, 89–103).

Olson depicts the results of its optimization which adjusts the relative locations of each of the plurality of nodes to minimize error associated with each of the individual nodes in Figure 4-14 (below).

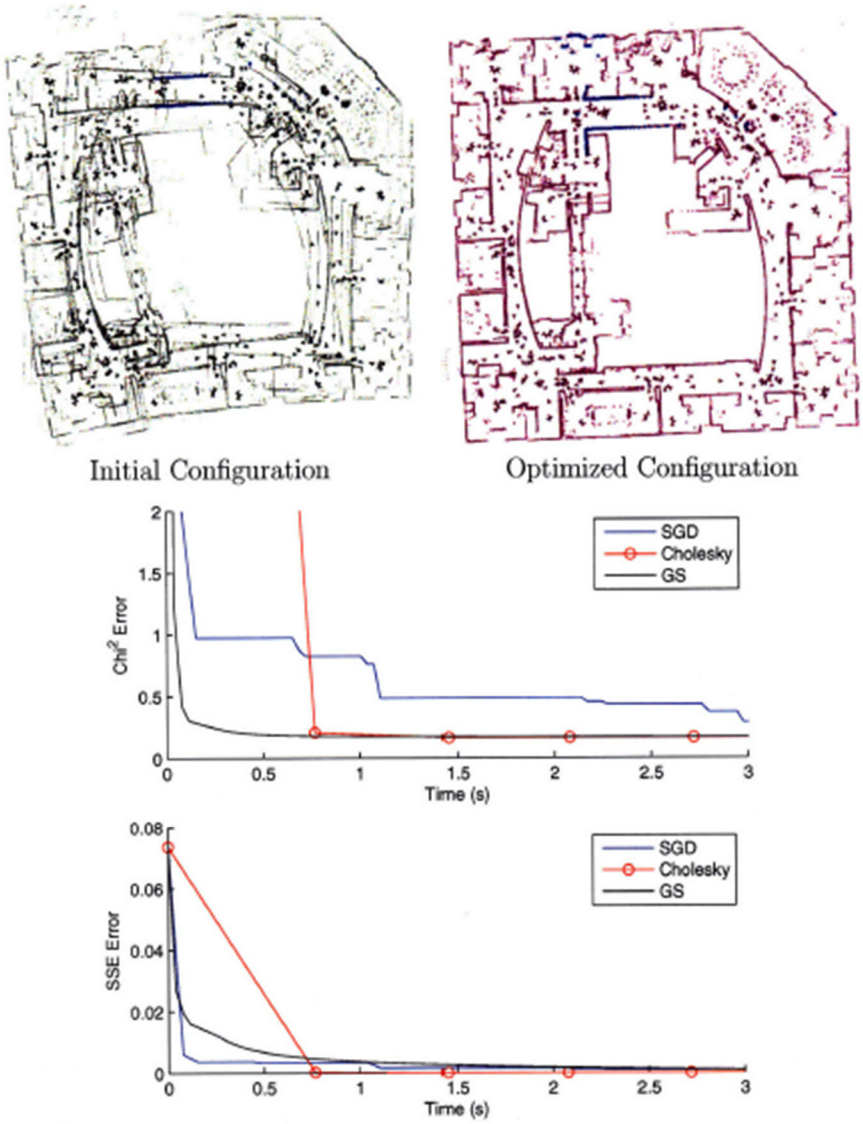


Figure 4-14: Intel Research Center. All the methods achieve very low error, though their convergence rates differ. Note that our method takes a quick and early lead in SSE error, though it lags in χ^2 error.

Ex1004, Figure 4-14.

Olson depicts its algorithm iteratively reducing the error, and increasing the confidences associated with each of the plurality of nodes, in Algorithm 7 (below).

Algorithm 7 SGD-Optimize-Graph

$\lambda = 1/3$
repeat
  Randomly permute order of *Constraints*
  {Update approximation $M = J^T\Sigma^{-1}J$. Let M_i be the i^{th} diagonal block.}
  for all $\{a, b, t_{ab}, \Sigma_{ab}\}$ in *Constraints* **do**
    compute R using Eqn. 4.15
    $W = R^T\Sigma_{ab}^{-1}R$
    for all $i \in [a+1, b]$ **do**
      $M_i = M_i + W$
      Update error-distribution trees with M
    end for
  end for
  $\Gamma = \max(\Sigma_i^{-1})$

  {Modified Stochastic Gradient Descent}
  for all $\{a, b, t_{ab}, \Sigma_{ab}\}$ in *Constraints* **do**
    $r = X_a^{-1} \oplus X_b$
    $r(3) = \text{mod2pi}(r(3))$
    compute R using Eqn. 4.15
    $s = -(b-a)\lambda R^T\Gamma^{-1}\Sigma_{ab}^{-1}r$
    $s_{max} = X_b - (X_a \oplus T_{ab})$
    $s = \text{clamp}(s, s_{max})$
    distribute$(a+1, b, s)$
  end for
  $\lambda = \lambda/(\lambda+1)$
until converged

Ex1004, Algorithm 7.

l. Claim 4

"The method of claim 2, wherein the associated confidences further includes, using a probability distribution indicative at least in-part of a probability that the respective node is in a respective location."

Olson discloses this limitation. Ex1003, ¶¶157–59. As explained in IV.A.2.f–g (Elements 2(a)–(b)), Olson discloses an algorithm which calculates confidence levels based on a probability distribution for each node in its graph. Ex1004, 12. This posterior distribution corresponds to a probability distribution indicative at least in-part of a probability that the respective node is in a respective location, which may "resemble radially-oriented ellipses." Ex1004, 118; *see also* Ex1004, 12–13, 20, 22–23, 32.

m. Claim 5

"The method of claim 1, wherein the constraining of the graph to the start and end locations includes constraining the graph to the start and end locations in view of a home locator."

Olson discloses this limitation. Ex1003, ¶¶160–63. As explained in IV.A.2.e, Olson discloses a method that implements "loop closing," which Olson explains "arises from the common case where a robot drives in a large loop, returning to its starting point" (constraining of the graph to the start and end positions . . . at a substantially similar location). Ex1004, 13. Olson further discloses the start and end

locations in view of a home locator. Ex1003, ¶161. For example, Olson explains that "[l]oop closing is related to place recognition," which may be enabled by the same algorithms "used by a robot to find a recharging station and properly align itself to it." Ex1004, 14, 29. Olson also describes multiple methods of detecting a home locator in an environment. Ex1003, ¶162. For example, Olson explains that a camera-based system may use SIFT to extract features (home locators), and then use a matching algorithm to determine the presence of features associated with it's the robot's starting position (start and end position in view of home locators), and so determine that the robot has returned to its starting position. Ex1004, 30, 34–35; Ex1003, ¶162. As another example, Olson explains that a robot may use "globally unique beacons" (synthetic home locators placed in the environment), like RFID tags, to enable loop closures in situations where such beacons may be practicably deployed. Ex1004, 30; Ex1003, ¶162.

n. Claim 6

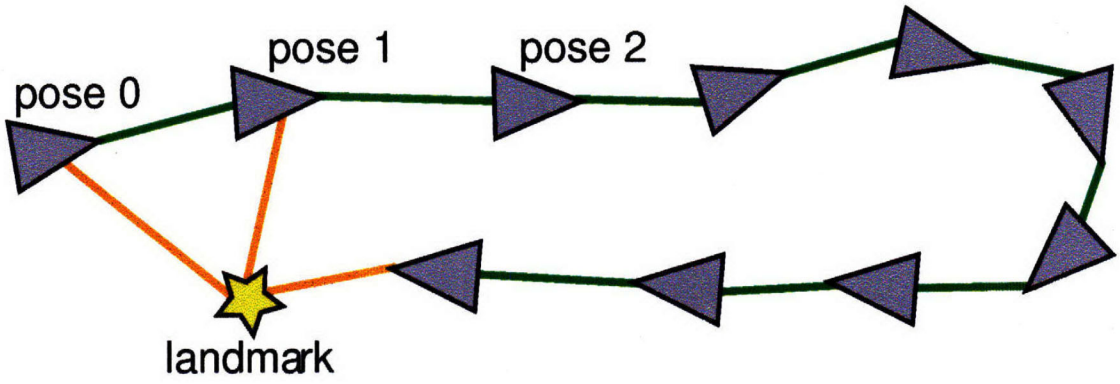
"The method of claim 1, wherein the traveling, by the robot, in the environment further includes, navigating the robot under user control."

Olson discloses this limitation. Ex1003, ¶¶164–65. For example, Olson explains that "[m]aps are also useful in non-autonomous applications," such as "when teleoperating a search-and rescue robot amidst rubble." Ex1004, 9.

o. Element 7[a]

"The method of claim 1, wherein the extended scan groups determined at least in part from groups of the plurality of nodes, further includes, selecting a root node as a reference location;"

Olson discloses this limitation. Ex1003, ¶¶167–176. As explained above in IV.A.2.d, Olson discloses performing scan matching on extended scan groups, the extended scan groups being determined in-part on at least two or more nodes of the plurality of nodes. Olson further discloses selecting a root node as a reference location. For example, Olson discloses a Pose/Feature graph wherein each pose corresponds to a position of the robot, and each pose is connected to an adjacent pose (node) by odometry data and visual data which provides information about the relative distance between poses, including to an initial location, and landmarks. Ex1004, 15, 20–21, 61–63; Ex1003, ¶¶169–71. Olson further discloses that its algorithm may calculate "global" position, x_{global}, by applying incremental data, x_{incr}, to a reference location such as the initial condition. Ex1004, 61–63; Ex1003, ¶¶172–75. Olson depicts this relationship in Figures 1-4, 2-2, and 4-2 (below). Olson discloses that it uses global position to compare its solutions to a known ground truth. Ex1004, 25–27, 44–46, 73–88.



Ex1004, Figure 1-4.

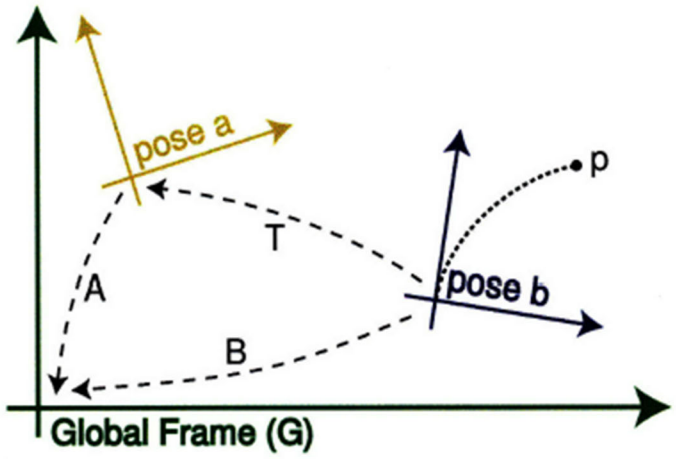


Figure 2-2: Coordinate transformations. Each robot pose represents a local coordinate system which can be related to the global coordinate by a rigid-body transform. Two local coordinate systems can also be related, e.g., $B = AT$. Point p, expressed with respect to coordinate frame B, can be projected to coordinate frame A by Ap and to the global coordinate frame by either Bp or ATp.

Ex1004, Figure 2-2.

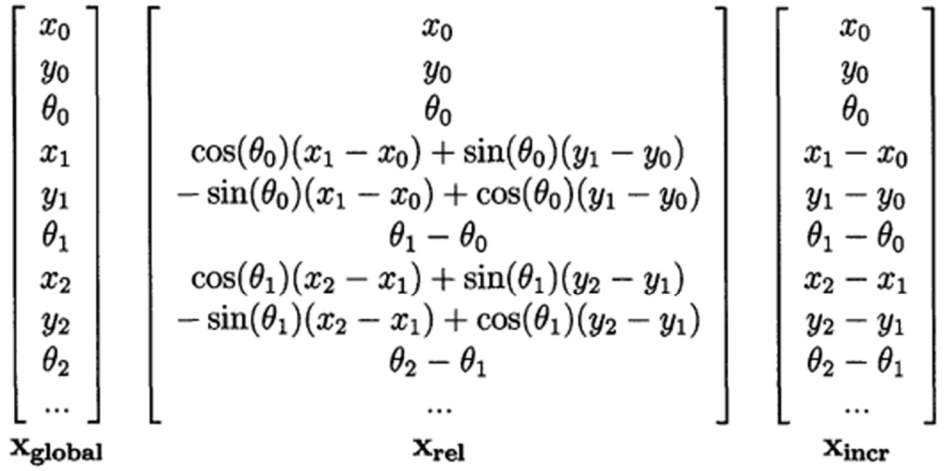


Figure 4-2: State Space Representations. The commonly used state space x_{global}, the rigid-body transformation state space x_{rel}, and our proposed "global incremental" state space x_{incr}.

Ex1004, Figure 4-2.

p. Element 7[b]

"finding overlap in measurements of distinct features in scans taken at least two of the respective nodes of the plurality of nodes, the root note [sic] is different from the respective node; and"

Olson discloses this limitation. Ex1003, ¶¶177–81. As explained above in IV.A.2.d, hereby incorporated by reference, Olson discloses using scan-matching, and explains that "scan-matching is the process of finding a rigid-body transformation that improves the alignment of two scans." Ex1004, 117; *see also* Ex1004, 31, 34, 119–22. Olson depicts calculation of a relative rigid-body transform between poses *a* and *b* (two respective nodes different from the root node) in Figure 2-2 (below). Olson explains that this is based on scan matching, saying "[g]iven . .

. ***sensor observations*** from pose *a* and *b*, the task is now to compute a rigid-body transformation that is likely to correctly align *a* and *b*." Ex1004, 34. Olson further explains that it repeats scan-matching "for every node in the graph." Ex1004, 35. Olson further explains that "[g]iven a pose [node] a, we wish to find all other poses [nodes] in the graph whose sensor readings might overlap those from pose [node] a". Ex1004, 32; Ex1003, ¶180. A POSITA would have understood that disclosure of inclusion of all nodes in the graph that have overlapping sensor measurements into an extended scan group discloses "at least two of the respective nodes of the plurality of nodes, the root note [sic] is different than the respective node." Ex1003, ¶180.

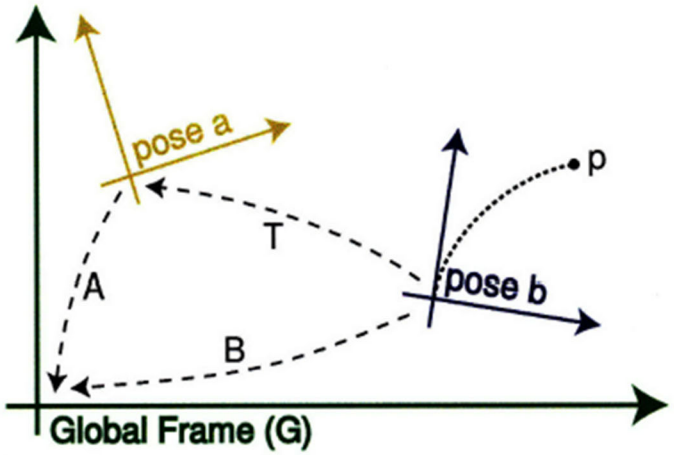


Figure 2-2: Coordinate transformations. Each robot pose represents a local coordinate system which can be related to the global coordinate by a rigid-body transform. Two local coordinate systems can also be related, e.g., $B = AT$. Point p, expressed with respect to coordinate frame B, can be projected to coordinate frame A by Ap and to the global coordinate frame by either Bp or ATp.

Ex1004, Figure 2-2.

q. Element 7[c]

"grouping the the [sic] at least two of the respective nodes into extended scan groups based at least in-part on overlapping distinct features of the scans at the at least two of the respective nodes."

Olson discloses this limitation. Ex1003, ¶¶182–85. As discussed in IV.A.2.d, Olson discloses grouping nodes into extended scan groups based on overlapping distinct features of the scans at the at least two of the respective nodes. Olson further discloses that "[t]he first step in identifying loop closure hypotheses is to identify those poses that might contain ***overlapping sensor readings***" (overlapping distinct features of the scans), the overlap being determined via scan matching. Ex1004, 32; Ex1003, ¶184. Olson explains that "[g]iven a pose [node] a, we wish to find all other poses [nodes] in the graph whose sensor readings might overlap those from pose [node] a" (overlapping distinct features of the scans). Ex1004, 32; Ex1003, ¶184.

r. Element 8[pre]

"A robot, comprising:"

To the extent the preamble is limiting, Olson discloses it. Ex1003, ¶¶186–90. Olson discusses examples of robots, basic functionalities of robots (such as collision avoidance and path planning), and explains that its mapping algorithm is designed to be integrated into robots. Ex1004, 9–12. Further, Olson discloses a system to

allow a robot to navigate around a new or unknown environment. Ex1004, 35–40.

Olson depicts several such robots in Figures 1-1, and 6-1 (below).

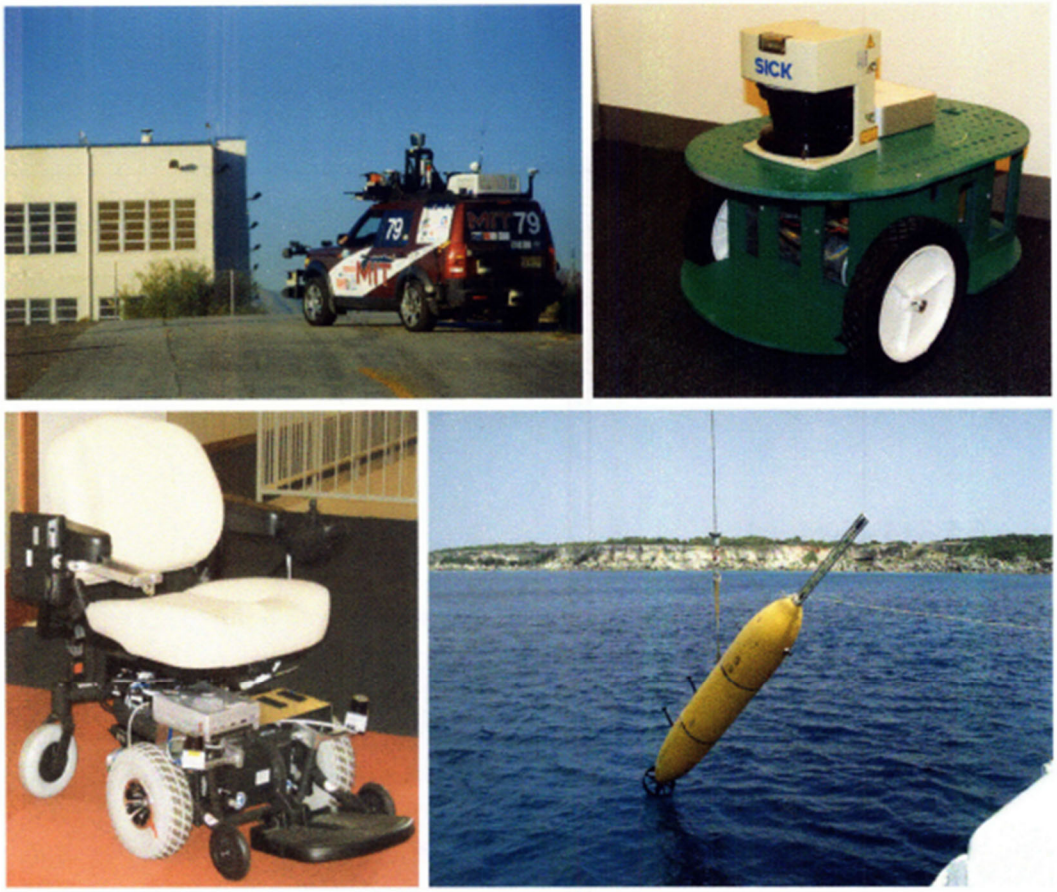


Figure 1-1: Robot Applications. Map building arises in many contexts, including autonomous cars [37], indoor surveying [68], underwater robots for ship-hull inspection [75], and human-centric assistive robotics [57].

Ex1004, Figure 1-1.

Figure 6-1: The author with several indoor robots.

Ex1004, Figure 6-1.

s. Element 8[a]

"a sensor configured to generate scans of an environment at a plurality of nodes, a respective node of the plurality of nodes is associated with a location in the environment; and"

Olson discloses this limitation as discussed above in IV.A.2.c (Element 1(b); incorporated herein by reference). Ex1003, ¶¶189–90.

t. Element 8[b]

"a mapping and localization unit configured to execute computer readable instructions to:"

Olson discloses this limitation. Ex1003, ¶¶191–95. Olson discloses that its robot performs mapping and localization functions. Ex1004, 9–16, 34–35, 55, 111; §§ IV.A.1.a–c. Olson discloses the use of a central processing unit ("CPU") to execute the computer readable instructions and perform the mapping and localization. Ex1004, 46. Olson also discusses the processing times needed by the CPU to execute the computer readable instructions. Ex1004, 49, 75. Olson also discusses ways to optimize CPU processing time. Ex1004, 94. A POSITA would have understood that these disclose a mapping and localization unit configured to execute computer readable instructions. Ex1003, ¶194.

u. Element 8[b][1]

"generate a graph of the plurality of nodes based at least in part on the generated scans;"

Olson discloses this limitation as discussed above in IV.A.2.c (Element 1(b); incorporated herein by reference). Ex1003, ¶¶196–97.

v. Element 8[b][2]

"determine extended scan groups in-part on at least two or more nodes of the plurality of nodes;"

Olson discloses this limitation as discussed above in IV.A.2.d (Element 1(c); incorporated herein by reference). Ex1003, ¶¶198–99.

w. Element 8[b][3]

"perform scan matching on the extended scan groups; and"

Olson discloses this limitation as discussed above in IV.A.2.d (Element 1(c); incorporated herein by reference). Ex1003, ¶¶200–01.

x. Element 8[b][4]

"constrain the graph between a start location and an end location, the start location and the end location being at a substantially similar location in the environment."

Olson discloses this limitation as discussed above in IV.A.2.e (Element 1(d); incorporated herein by reference). Ex1003, ¶¶202–03.

y. Claim 9

"The robot of claim 8, wherein the mapping and localization unit is further configured to execute computer readable instructions to, determine confidences associated with the location in the environment of each node of the plurality of nodes."

Olson discloses this limitation as discussed above in IV.A.2.g (Element 2(b); incorporated herein by reference). Ex1003, ¶¶204–05.

z. Claim 10

"The robot of claim 9, wherein the mapping and localization unit is further configured to execute computer readable instructions to, generate a cost function based at least in-part on the confidences and the location of each node of the plurality of nodes, the location of each node in the graph being determined based on solving the cost function for a minimum value."

Olson discloses this limitation as discussed above in IV.A.2.j–k (Claim 3; incorporated herein by reference). Ex1003, ¶¶206–07.

aa. Claim 11

"The robot of claim 8, wherein the mapping and localization unit is further configured to execute computer readable instructions to, render a map from the graph, the map based at least in-part on ray tracings of the scans."

Olson discloses this limitation as discussed above in IV.A.2.i (Element 2(d); incorporated herein by reference). Ex1003, ¶¶208–09.

bb. Claim 12

"The robot of claim 8, further comprising: an actuator configured to move the robot between locations in the environment."

Olson discloses this limitation as discussed above in IV.A.2.b (Element 1(a); incorporated herein by reference). Ex1003, ¶¶210–12. A POSITA would have understood that the claimed actuator is a mechanical means for moving the robot, as disclosed with respect to Element 1(a). Ex1001, 8:44–48, 10:45–55, FIG. 3; Ex1003, ¶212.

cc. Claim 13

"The robot of claim 8, further comprising: a user interface for controlling the robot by at least one user."

Olson discloses this limitation. Ex1003, ¶¶213–215. As explained in IV.A.2.n, Olson discloses a robot navigating under the control of a user. A POSITA would have understood that disclosure of a robot navigating under the control of a user also discloses a means for controlling the robot (a user interface). Ex1003, ¶214.

dd. Claim 14

"The robot of claim 8, further comprising: a navigation unit configured to navigate the robot autonomously without the user."

Olson discloses this limitation. Ex1003, ¶¶216–21. As explained in IV.A.2.t, Olson discloses a navigation and mapping unit. Olson further discloses that its robot comprises a navigation unit configured to navigate the robot autonomously. Ex1003, ¶¶217–20. For example, Olson explains that "map building is a critical component of every ***autonomous robot***, particularly if they must operate in unfamiliar environments." Ex1004, 9. Olson depicts several robots which build maps to navigate autonomously in Figure 1-1 (below).

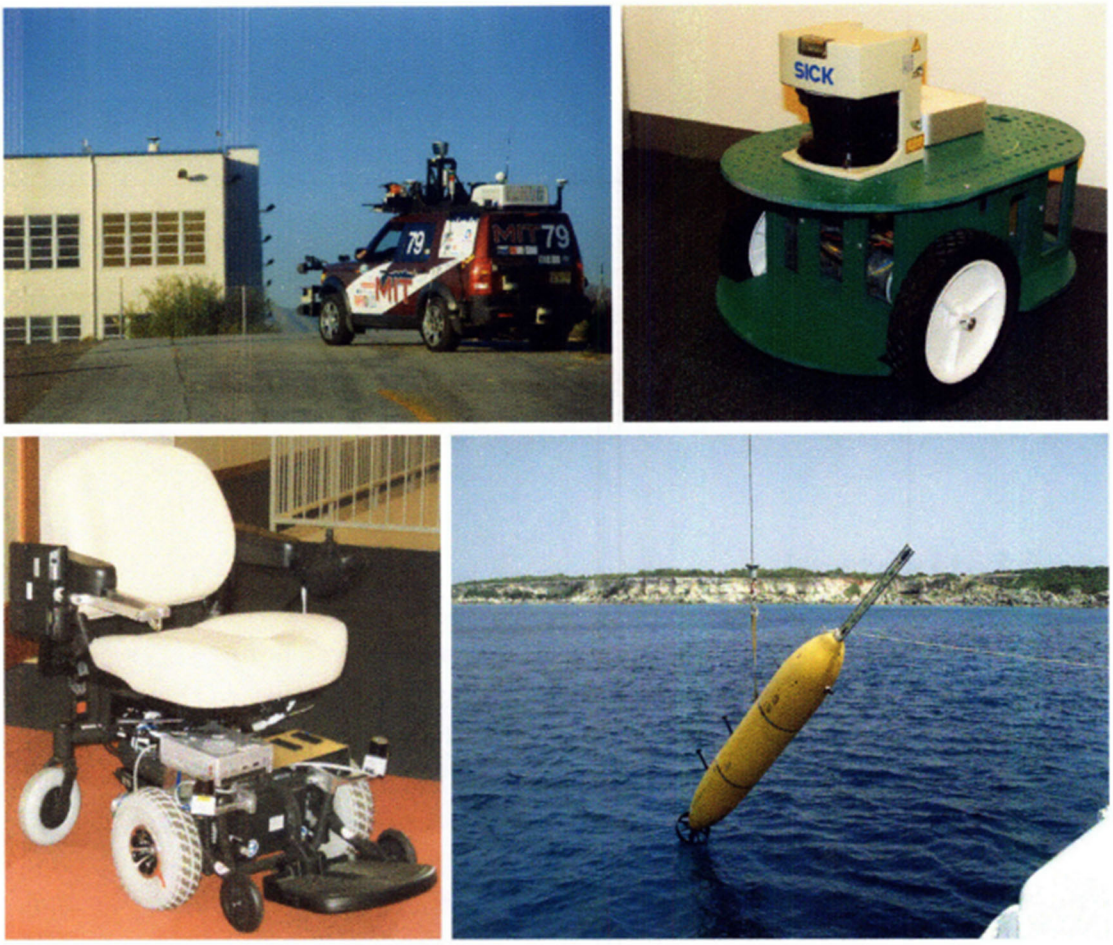


Figure 1-1: Robot Applications. Map building arises in many contexts, including autonomous cars [37], indoor surveying [68], underwater robots for ship-hull inspection [75], and human-centric assistive robotics [57].

Ex1004, Figure 1-1.

Olson further discloses that at least one of its data sets came from a vehicle that navigated autonomously while mapping. Ex1004, 44, 109 ("Our vision data was collected by MIT's DARPA Grand Challenge vehicle (see Fig. A-1 [below]) during an autonomous run of the National Qualifying event.").

Figure A-1: Talos. Our vision test-bed was MIT's DARPA Grand Challenge vehicle. The vehicle has five cameras (two forward, left, right, rear), and a high-quality IMU/GPS system for both dead-reckoning and ground-truthing.

Ex1004, Figure A-1.

ee. Element 15[pre]

"A non-transitory computer-readable medium having computer readable instructions stored thereon, that when executed by at least one processor, configure the at least one processor to:"

Olson discloses this limitation. Ex1003, ¶¶222–25. Olson discloses the use of a central processing unit ("CPU") to execute the computer readable instructions and perform the mapping and localization. Ex1004, 46. Olson also discusses the processing times needed by the CPU to execute the computer readable instructions. Ex1004, 49, 75. Olson also discusses ways to optimize CPU processing time. Ex1004, 94. A POSITA would have understood that these disclose this limitation. Ex1003, ¶224.

ff. Element 15[a]

"transmit a signal to at least one sensor to generate scans of an environment at a plurality of nodes, a respective node of the plurality of nodes being associated with a location in the environment;"

Olson discloses this limitation. Ex1003, ¶¶226–29. As explained in IV.A.2.c, Olson discloses a respective node of the plurality of nodes corresponds to (being associated with) a scan generated by a sensor of the robot at a location in the environment. A POSITA would have understood that a robot configured to take scans at a plurality of nodes transmits a signal to those sensors instructing the sensors to generate scans. Ex1003, ¶228.

gg. Element 15[b]

"generate a graph of the plurality of nodes based in-part on the generated scans;"

Olson discloses this limitation as discussed above in IV.A.2.c, u (Elements 1(b), 8(b)(1); incorporated herein by reference). Ex1003, ¶¶230–31.

hh. Element 15[c]

"determine extended scan groups based at least in part on two or more nodes of the plurality of nodes;"

Olson discloses this limitation as discussed above in IV.A.2.d, v (Elements 1(c) and 8(b)(2); incorporated herein by reference). Ex1003, ¶¶232–33.

ii. Element 15[d]

"perform scan matching on the extended scan groups; and"

Olson discloses this limitation as discussed above in IV.A.2.d, w (Elements 1(c) and 8(b)(3); incorporated herein by reference). Ex1003, ¶¶234–35.

jj. Element 15[e]

"constrain the graph between a start location and an end location, the start location and the end location being at a substantially similar location."

Olson discloses this limitation as discussed above in IV.A.2.e, x (Elements 1(d) and 8(b)(4); incorporated herein by reference). Ex1003, ¶¶236–37.

kk. Claim 16

"The non-transitory computer-readable medium of claim 15, wherein each extended scan group includes at least three or more scans."

Olson discloses this limitation. Ex1003, ¶¶238–240. As explained in IV.A.2.d, o–q, Olson discloses scan-matching between nodes within extended scan groups. Olson further explains that an extended scan group includes "***all*** other poses in the graph whose sensor readings might overlap." Ex1004, 32. A POSITA would have understood that disclosure of "all other poses" without limitation discloses "each extended scan group includes at least three or more scans." Ex1003, ¶239.

ll. Claim 17

"The non-transitory computer-readable medium of claim 15, wherein the at least one processor is further configured to execute the computer readable instructions to, determine a cost function based at least in-part on confidences associated with the location of each node of the plurality of nodes."

Olson discloses this limitation as discussed above in IV.A.2.j, z (Element 3(a) and Claim 10; incorporated herein by reference). Ex1003, ¶¶241–42.

mm. Claim 18

"The non-transitory computer-readable medium of claim 17, wherein the at least one processor is further configured to execute the computer readable instructions to, generate a map based at least in-part on minimizing the cost function."

Olson discloses this limitation as discussed above in IV.A.2.k, z (Element 3(b) and Claim 10; incorporated herein by reference). Ex1003, ¶¶243–44.

B. Ground 2: Anticipation by Stachniss

As explained below and in further detail in the Declaration of Dr. Karam, Stachniss discloses all elements of claims 1–18 of the '325 Patent.

1. Overview of Ground and Prior Art

Stachniss is a "comprehensive introduction to the *simultaneous localization and mapping problem*," or SLAM, which "is generally regarded as one of the most important problems in the pursuit of building truly autonomous mobile robots."

Ex1005, 1153. It describes several SLAM methods, including "Graph-Based Optimization Techniques," as employed in the '325 Patent. Ex1005, 1162–66. It further explains how visual data and range data may be used in combination with SLAM to supplement traditional odometry sensors, identify loop-closures, and ultimately build pictorial maps of different environments. Ex1005, 1166–19.

Stachniss further explains, with respect to graph-based techniques, "[l]andmarks and robot locations can be thought of as nodes in a graph. Every consecutive pair of locations x_{t-1}, x_t is tied together by an edge that represents the information conveyed by the odometry reading u_t." Ex1005, 1162, Figure 46.7.

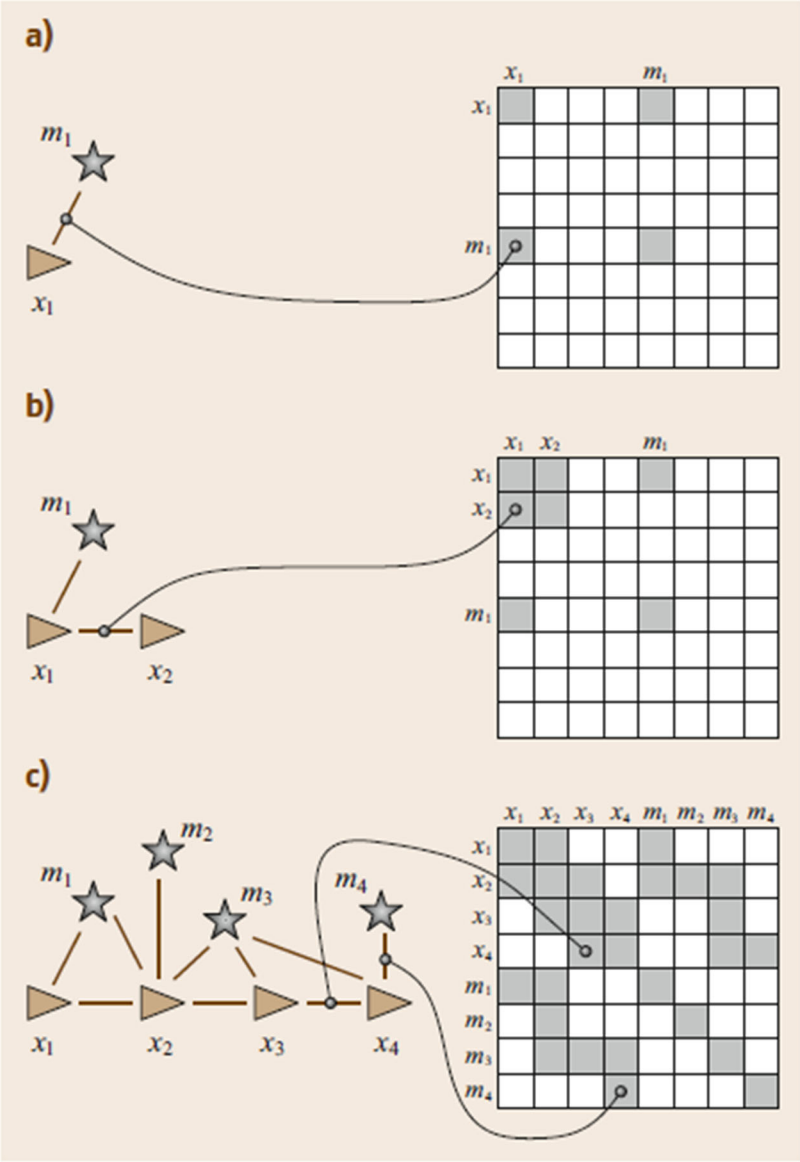


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

Stachniss further discloses extended scan groups, or groups of nodes whose associated sensor measurements observe overlapping features, as in the ’325 Patent. For example, Stachniss explains that overlapping camera measurements from different poses enable “visual odometry, including feature detection, feature matching, outlier rejection, and constraint estimation, and trajectory optimization.” Ex1005, 1168.

Stachniss also discloses constraining the graph to start and end at a similar location, just like the ’325 Patent. For example, Stachniss discloses a robot that refines its estimate and the uncertainty associated with its estimate of both its own position and the position of landmarks in the environment when it encounters the first landmark again. Ex1005, 1158, Figure 46.2 (below).

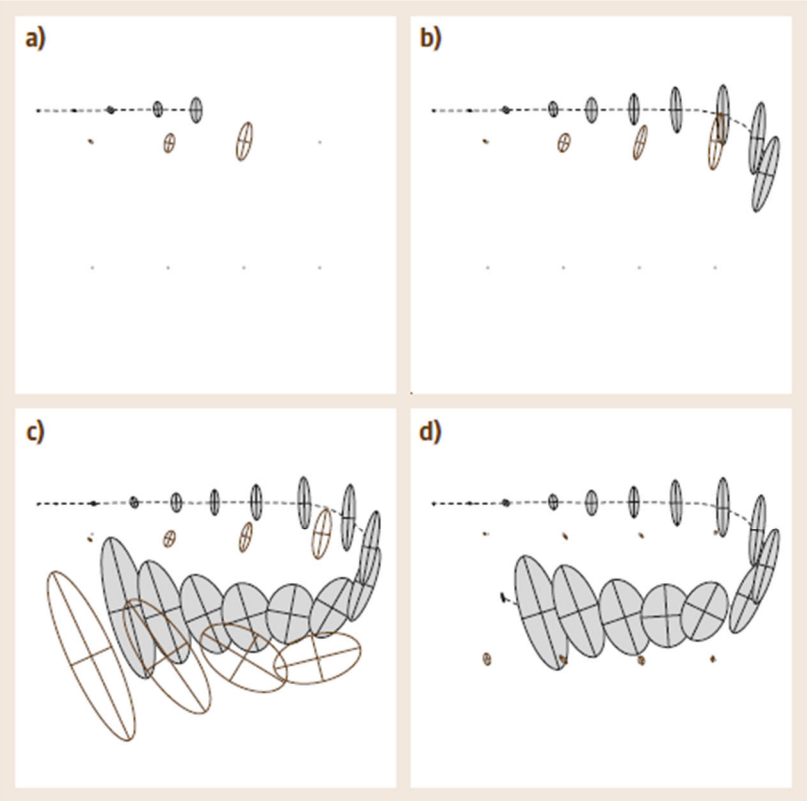


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the robot's positional uncertainty is increasing, as is its uncertainty about the landmarks it encounters. In (d) the robot senses the first landmark again, and the uncertainty of *all* landmarks decreases, as does the uncertainty of its current pose (image courtesy of Michael Montemerlo, Stanford University)

Ex1005, Fig. 46.2.

2. Detailed Analysis of Ground 2

a. Element 1[pre]

To the extent the preamble is limiting, Stachniss discloses it. Ex1003, ¶¶246–52. Stachniss discloses a method that enables a robot to generate a map of an environment as it traverses the environment. Ex1005, 1153–54, 1160, 1162–66. Stachniss explains that this class of methods are referred to as "Simultaneous Localization and Mapping" (SLAM) methods, and that SLAM is "one of key enabling technologies of robot navigation." Ex1005, 1153–54. Stachniss provides

several examples of maps generated with SLAM techniques, including in Fig. 46.11 (below).

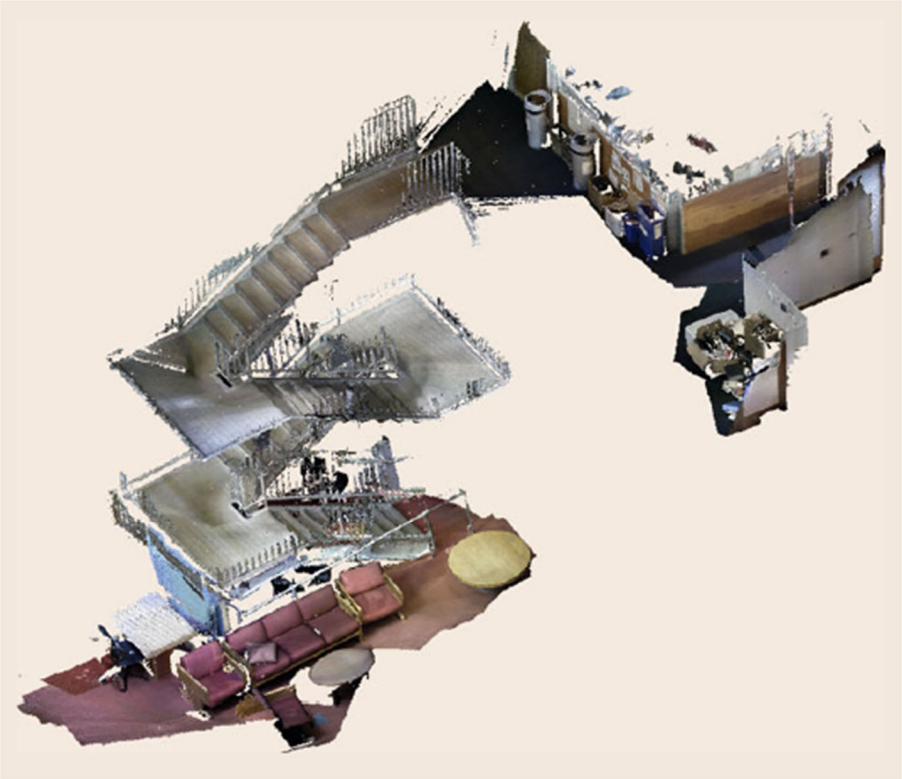


Fig. 46.11 Spatially extended KinectFusion output produced in real-time with Kintinuous (after [46.139])

Ex1005, Fig. 46.11.

b. Element 1[a]

Stachniss discloses this limitation. Ex1003, ¶¶253–58. Stachniss discloses that its robot travels in the environment before, during, and after the map is created. For example, Stachniss explains that robots moves through the environment to a "sequence of locations," X_T, where odometry sensors, such as wheel encoders or motor controllers, "provide[] relative information between two consecutive

locations," U_T., and the robot "senses objects ***in the environment***," collecting sensor data in Z_T, where the sensors detect the environment, m, and landmarks, m_i. Ex1005, 1154; Fig. 46.1 (below), Fig. 46.7 (below).

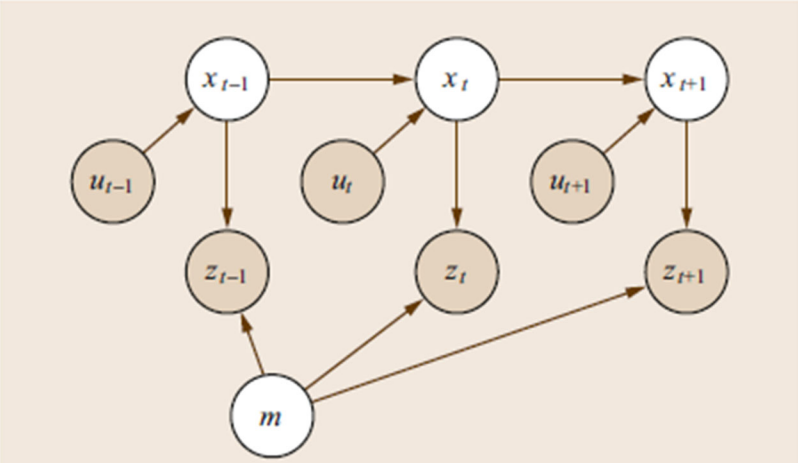


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

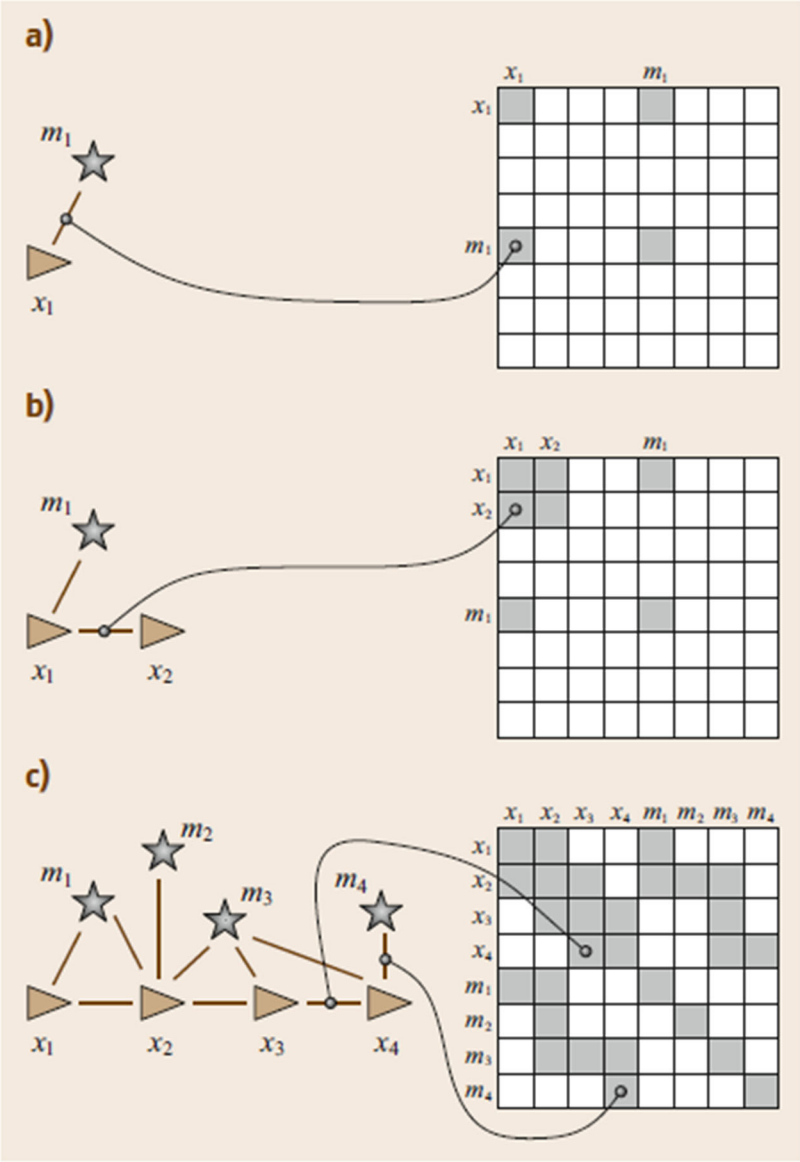


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

c. Element 1[b]

Stachniss discloses this limitation. Ex1003, ¶¶259–63. Stachniss discloses a method of mapping an environment wherein "[l]andmarks and robot locations can be thought of as nodes in a graph." Ex1005, 1162–66. Stachniss further explains that sensor data, z_i, is collected at each node, i, and is collected into the vector Z_T. Ex1005, 1153–54. Stachniss depicts this relationship in Fig. 46.7 (below).

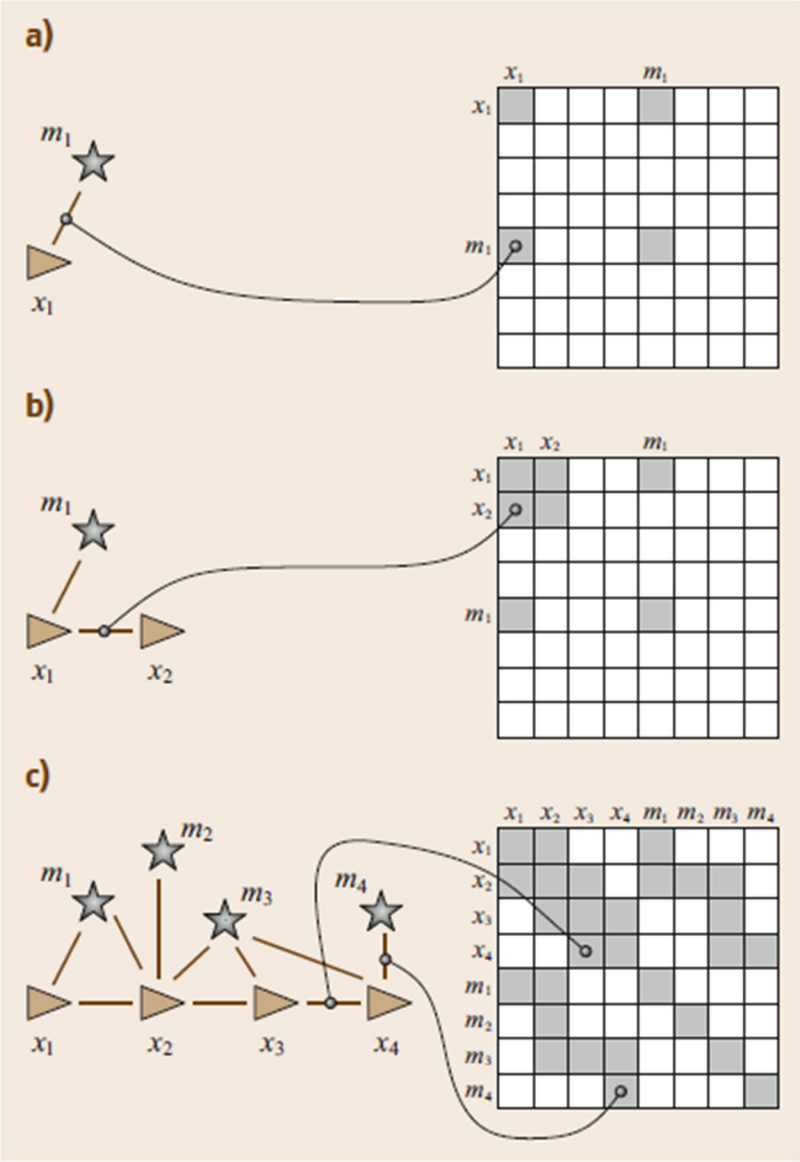


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

d. Element 1[c]

Stachniss discloses this element. Ex1003, ¶¶264–69. For example, Stachniss discloses that visual SLAM techniques estimate relative distance between nodes by performing scan-matching using "feature detection, feature matching, outlier rejection, and trajectory optimization." Ex1005, 1168; Ex1003, ¶266. Indeed, Stachniss discloses that others had performed these techniques in robotic mapping contexts, and described an approach using example SURF and RANSAC as "fairly standard." Ex1005, 1165.

Stachniss also discloses that these techniques allow the algorithm to estimate the relative positions of two or more nodes (extended scan groups) based on mutual detection of the same landmark, as depicted in Fig. 46.7 (below), where *x1* and *x2* each detect landmark *m1*, and x_2, x_3, and x_4 each detect landmark m_3. Ex1005, 1163; Ex1003, ¶267.

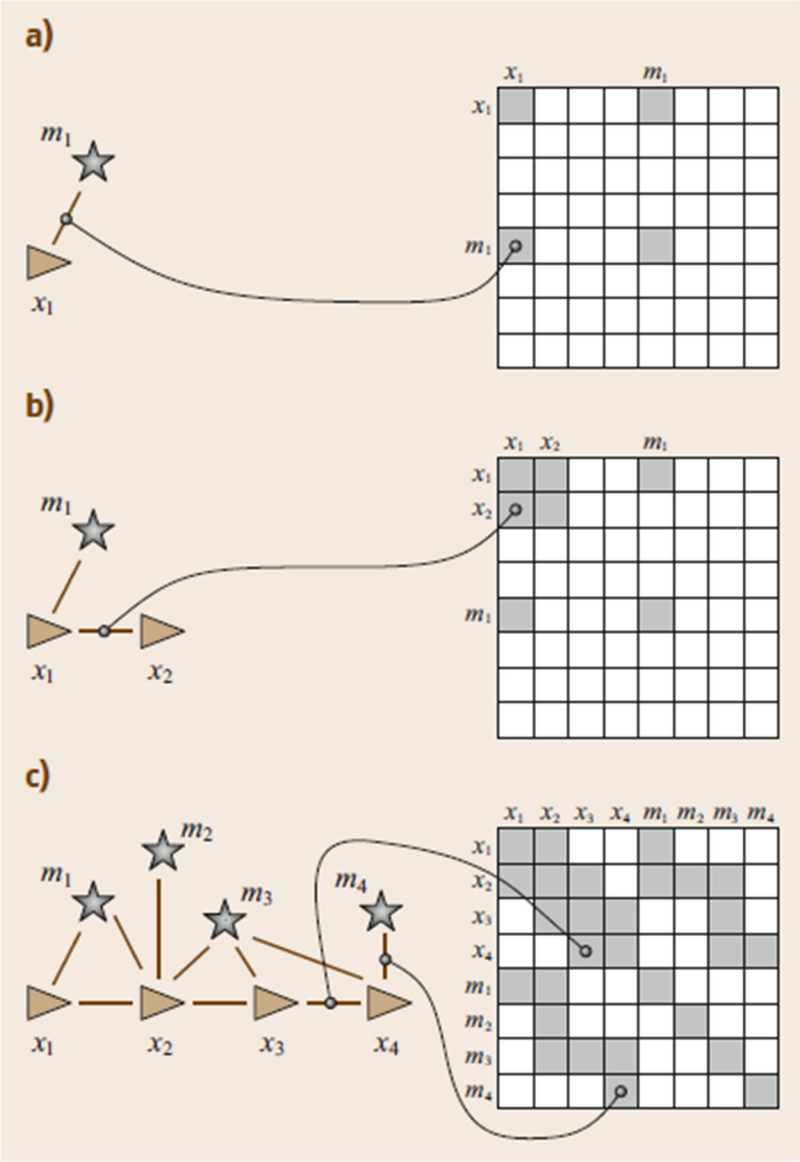


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

Stachniss further discloses that some methods, like "Hierarchical SLAM," define "independent local maps" (extended scan groups) based on detection of overlapping features within the group, which "may be merged in case of re-visiting a place." Ex1005, 1163–64; Ex1003, ¶268.

e. Element 1[d]

Stachniss discloses this limitation. Ex1003, ¶¶270–74. Stachniss discloses that its method may include a loop closure, which imposes corresponding constraints, when it determines it has "reach[ed] the same location" (a substantially similar location). Ex1005, 1156–58; Ex1003, ¶¶271–72. Stachniss depicts a loop closure in Figure 46.2, where, once the robot senses the first landmark again, the robot imposes an additional edge (constraint) between the start and end nodes (positions of the robot), and then performs an optimization that modifies the estimated locations of each node. Ex1005, 1158; Ex1003, ¶273.

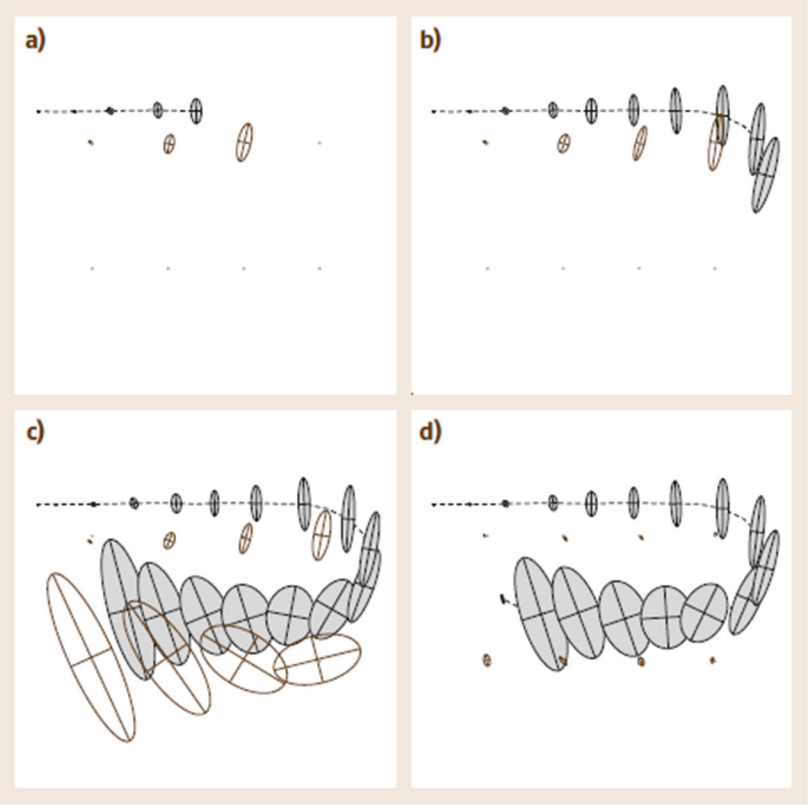


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the robot's positional uncertainty is increasing, as is its uncertainty about the landmarks it encounters. In (d) the robot senses the first landmark again, and the uncertainty of *all* landmarks decreases, as does the uncertainty of its current pose (image courtesy of Michael Montemerlo, Stanford University)

Ex1005, Fig. 46.2.

f. Element 2[a]

Stachniss discloses this limitation. Ex1003, ¶¶275–81. For example, Stachniss explains that SLAM methods generate a map by determining the most-probable locations of the robot and the landmarks given the data. Ex1005, 1155, 1157–57, 1163; Ex1003, ¶276. Stachniss also explains that this maximum likelihood map may be expressed in terms of the probability distribution (range) or each node, which in turn may depend on "feature observation" (scan matching), as

shown in Equation 46.18 (below) for a graph-based SLAM approach. Ex1005, 1163; Ex1003, ¶¶277–78.

$$\log p(X_T, m \mid Z_T, U_T) = \text{const}$$
$$+ \sum_t \underbrace{[x_t - g(x_{t-1}, u_t)]^{\mathrm{T}} R_t^{-1} [x_t - g(x_{t-1}, u_t)]}_{\text{odometry reading}}$$
$$+ \sum_t \underbrace{[z_t - h(x_t, m)]^{\mathrm{T}} Q_t^{-1} [z_t - h(x_t, m)]}_{\text{feature observation}}. \qquad (46.18)$$

Stachniss depicts a range associated with the uncertainty of the position of each node for both poses and landmarks in Figure 46.2 (below), in the context of an EKF mapping algorithm. Ex1005, 1164–65 (explaining that filter-based methods have been used to refine portions of large maps built using graph-based methods); Ex1003, ¶279.

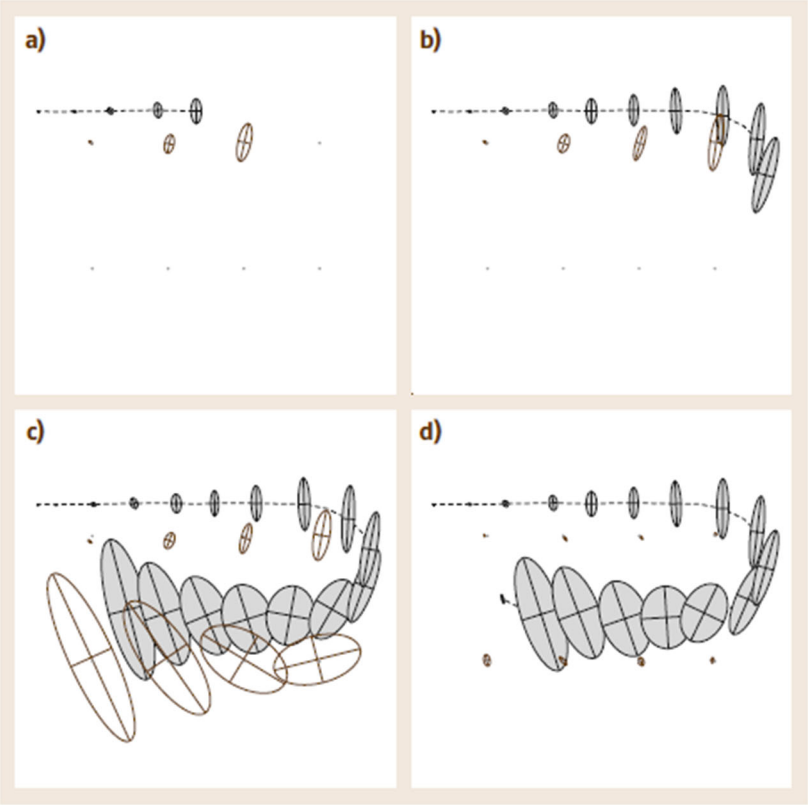


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the robot's positional uncertainty is increasing, as is its uncertainty about the landmarks it encounters. In (d) the robot senses the first landmark again, and the uncertainty of *all* landmarks decreases, as does the uncertainty of its current pose (image courtesy of Michael Montemerlo, Stanford University)

Ex1005, Fig. 46.2.

The dotted line represents the robot's route in an unknown environment, and the shaded ellipses represent a range associated with the confidence in the robot's location at each measurement point. Ex1005, 1157–58; Ex1003, ¶280. As the robot moves, its location grows more uncertain, which is depicted by the size of the ellipses. Ex1005, 1157–58; Ex1003, ¶280. As the robot senses the landmarks (represented by dots), it marks them with their own ranges of uncertainty. Ex1005, 1157–58; Ex1003, ¶280. As seen in Figure 46.2.d, once the robot senses the first

landmark again, the uncertainty of its stored locations and the locations of the landmarks decrease. Ex1003, ¶280.

g. Element 2[b]

Stachniss discloses this limitation. Ex1003, ¶¶282–88. As explained in IV.B.2.f with respect to element 2[a], Stachniss discloses that each node in the graph comprises a range of possible locations based on the uncertainty associated with the pose. For example, Stachniss discloses a probability distribution of the location of each pose-node in Equation 46.9 (below). Ex1003, ¶284.

$$p(x_t \mid x_{t-1}, u_t) = \mathcal{N}(g(x_{t-1}, u_t), \mathbf{R}_t) \,. \qquad (46.9)$$

Stachniss further discloses that, for a sensor-based graph-SLAM method, each node has an uncertainty dependent on the uncertainty of odometry data and of visual sensor data. Ex1005, 1157, 1163; Ex1003, ¶285.

Stachniss further depicts each node having an uncertainty corresponding to a range of possible locations for poses and landmarks in Figure 46.2 (below). Ex1005, 1155, 1157–58, 1163; Ex1003, ¶286.

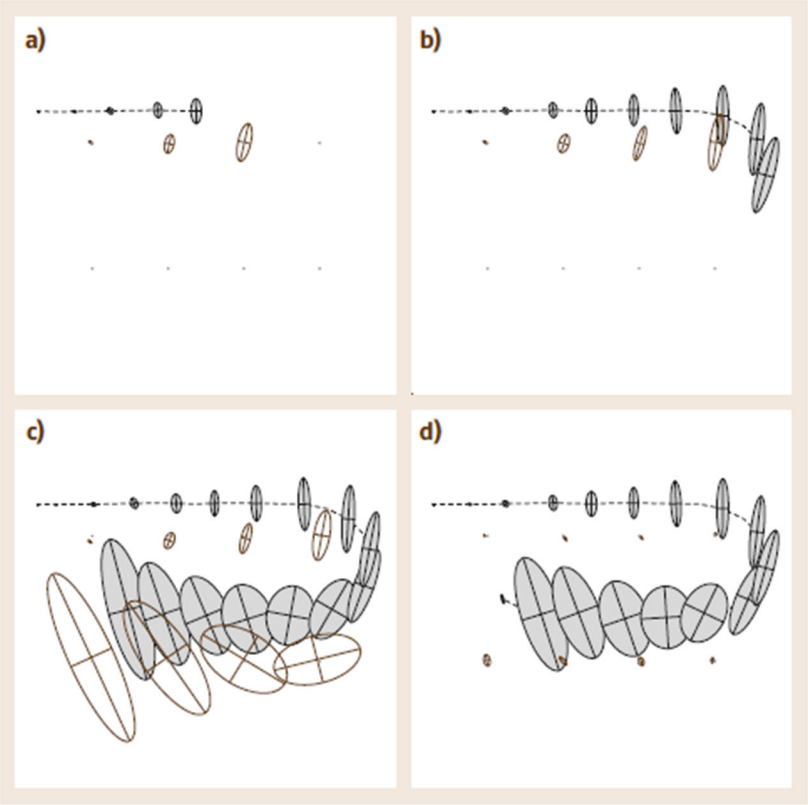


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the robot's positional uncertainty is increasing, as is its uncertainty about the landmarks it encounters. In (d) the robot senses the first landmark again, and the uncertainty of *all* landmarks decreases, as does the uncertainty of its current pose (image courtesy of Michael Montemerlo, Stanford University)

Ex1005, Fig. 46.2.

The '325 Patent variously explains that "[t]he confidence can be based at least in part on the ranges," Ex1001, 21:1–2, "[t]he confidence can be represented as a covariance matrix," Ex1001, 21:38–39, and "confidence can also be represented with other statistical indicia known in the art, such as variances, sample variances, correlations, etc.," Ex1001, 21:44–47. A POSITA would have understood that Stachniss's disclosures disclose the confidences described and claimed in the '325 Patent. Ex1003, ¶287.

h. Element 2[c]

Stachniss discloses this limitation. Ex1003, ¶¶289–92. For example, Stachniss explains that "Graph-Based Optimization Techniques" "solve[] the SLAM problem [find a location of the plurality of nodes] through nonlinear sparse optimization." Ex1005, 1162; Ex1005, 1153–54, 1157, 1162, 1166; Ex1003, ¶290. Stachniss further explains that this optimization is applied to the "quadratic form" of the "log-posterior [based at least in-part on the confidences] of the full SLAM problem." Ex1005, 1163; Ex1003, ¶291.

i. Element 2[d]

Stachniss discloses this limitation. Ex1003, ¶¶293–98. As discussed in IV.B.2.h, Stachniss discloses generating a map from the optimized graph. Stachniss further discloses that its method is able to account for "partial observability," and uses detection of landmarks from multiple points to improve its estimate of a landmark's position. Ex1005, 1158–59, Fig. 46.7. A POSITA would understand that each of these involves the claimed ray-tracing. Ex1003, ¶294.

Stachniss further discloses particle methods in which, "[w]hen a [sensor] measurement z_t is received . . . FastSLAM computes for each particle the probability of the new measurement . . . and then FastSLAM draws with replacement from the set of existing particles a new set of particles." Ex1005, 1159. In one variant, "the

Gaussians used to model point landmarks are replaced by an occupancy grid." Ex1005, 1161. In such instances, the probability that a cell is occupied is estimated based on each scan, which a POSITA would have understood involves estimating the probability that a cell is unoccupied based on observing a feature beyond that cell that would be occluded if the cell were occupied. Ex1005, 1161; Ex1003, ¶¶295–96. This is consistent with the '325 Patent's description of one embodiment of ray-tracing. Ex1001, 22:22–34; Ex1003, ¶297. Stachniss depicts an example of a map generated using an occupancy grid approach with laser scans in Figure 46.5 (below).

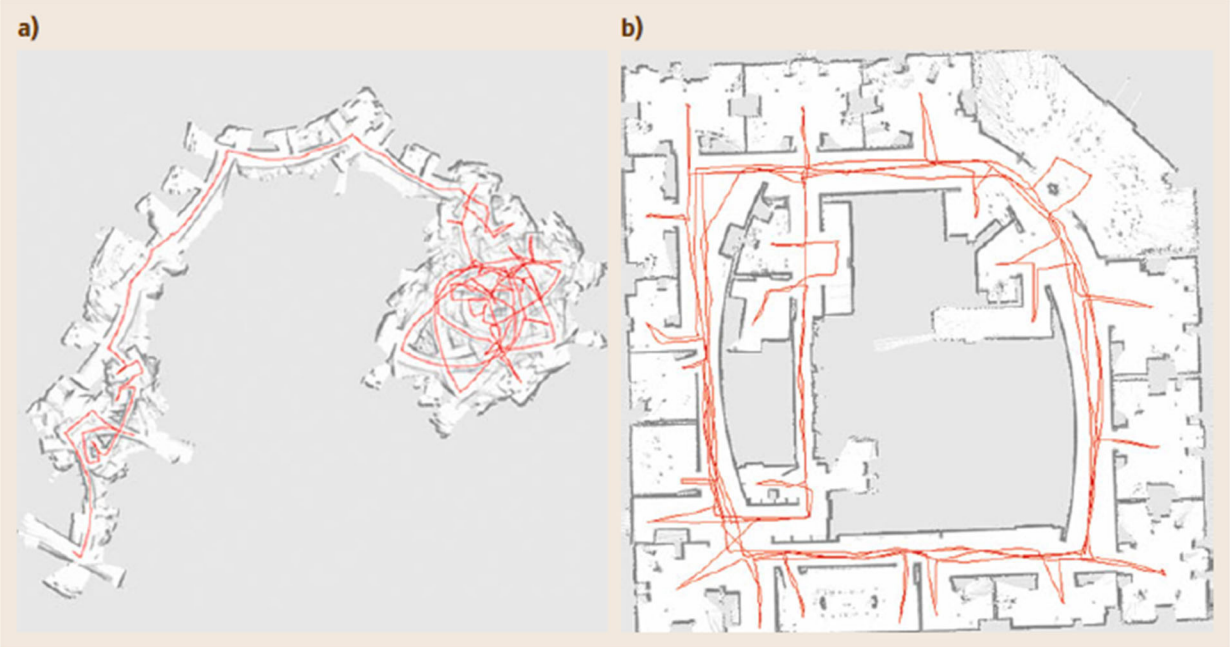


Fig. 46.5 Occupancy grid map generated from laser range data and based on pure odometry (image courtesy of Dirk Hähnel, University of Freiburg)

Ex1005, Fig. 46.5.

j. Element 3[a]

Stachniss discloses this limitation. Ex1003, ¶¶299–303. For example, Stachniss explains that, in graph-based SLAM, "[i]f we think of the graph as a spring-mass model [], computing the SLAM solution is equivalent to computing the state of minimal energy of this model." Ex1005, 1163. Stachniss further explains that the "state of minimal energy" "corresponds to the log-posterior of the full SLAM problem," as represented in Equation 46.18 (below), which includes in its definition x_t (the relative locations of each of the plurality of nodes) and the expressions within each sum (the confidences associated with each of the plurality of nodes). Ex1005, 1154–56, 1163; Ex1003, ¶¶300–02.

$$\log p(X_T, m \mid Z_T, U_T) = \text{const} + \sum_t \underbrace{[x_t - g(x_{t-1}, u_t)]^{\mathrm{T}} R_t^{-1} [x_t - g(x_{t-1}, u_t)]}_{\text{odometry reading}} + \sum_t \underbrace{[z_t - h(x_t, m)]^{\mathrm{T}} Q_t^{-1} [z_t - h(x_t, m)]}_{\text{feature observation}}. \quad (46.18)$$

Stachniss further explains that this form "yields a sparse system of equations [a cost function] and a number of efficient optimization techniques can be applied," including "gradient descent." Ex1005, 1163; Ex1003, ¶301. Stachniss later explains that "robust cost function[s] are used for SLAM." Ex1005, 1164.

k. Element 3[b]

Stachniss discloses this limitation. Ex1003, ¶¶304–308. As explained in IV.B.2.j, Stachniss discloses a cost function associated with finding the maximum likelihood map. For example, Stachniss explains that optimization proceeds by finding a "minimum energy" (minimum value) of the system. Ex1003, 1163; Ex1003, ¶305. As a further example, Stachniss explains that the cost function may be optimized using "gradient descent [cost function minimization]." Ex1005, 1163; Ex1003, ¶306. A POSITA would have understood that this discloses finding a minimum value for the cost function. Ex1003, ¶307.

l. Claim 4

Stachniss discloses this limitation. Ex1003, ¶¶309–13. As explained in VI.B.2.g, Stachniss discloses nodes associated with confidences. Stachniss further discloses that these confidences "characterize[] the ***probability distribution*** of the location [node] x_t." Ex1005, 1155, 1157–58, 1163. Stachniss further discloses that the probability distribution may be modeled as a Gaussian distribution (a probabilistic distribution). Ex1005, 1158, 1166; Ex1003, ¶¶310–12. Stachniss depicts probability distributions indicative at least in-part of a probability that the respective node is in a respective location in Figure 46.2 (below). Ex1003, ¶312.

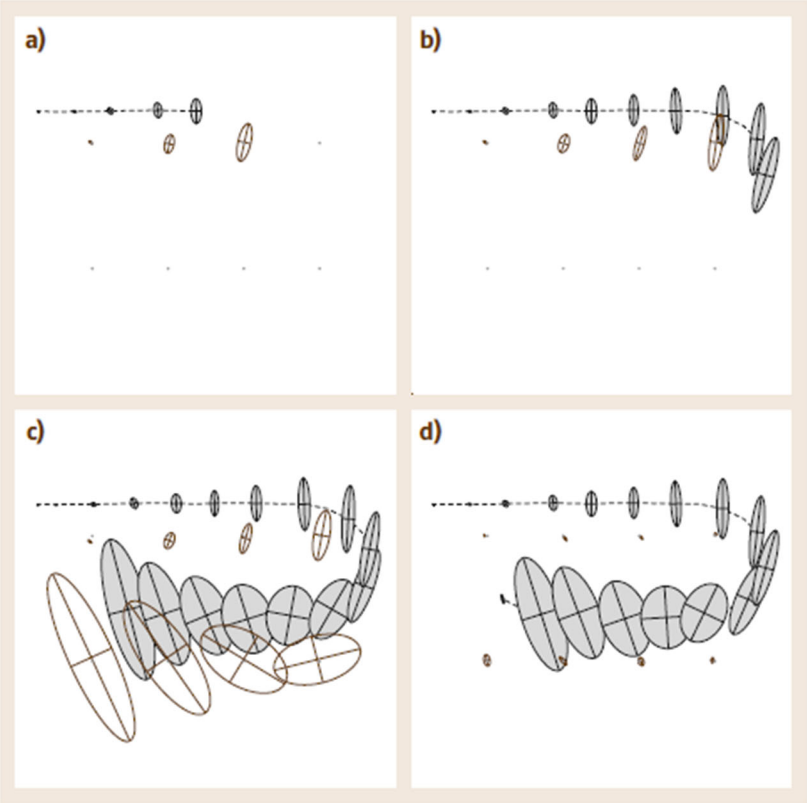


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the robot's positional uncertainty is increasing, as is its uncertainty about the landmarks it encounters. In (d) the robot senses the first landmark again, and the uncertainty of *all* landmarks decreases, as does the uncertainty of its current pose (image courtesy of Michael Montemerlo, Stanford University)

Ex1005, Fig. 46.2.

m. Claim 5

Stachniss discloses this limitation. Ex1003, ¶¶314–319. As explained in IV.B.2.e, Stachniss discloses that its method may include a loop closure, which imposes corresponding constraints, when it determines it has "reach[ed] the same location" (a substantially similar location). Ex1005, 1156–58; Ex1003, ¶316. Stachniss further discloses a method for determining whether a landmark (home locator) detected from a later node in the graph is the same as the landmark detected

at an earlier position by imposing a "soft correspondence constraint," as described in Equation 46.19. Ex1003, ¶317.

$$(m_j - m_i)^T \boldsymbol{\Gamma} (m_j - m_i) . \qquad (46.19)$$

Equation 46.19 imposes a cost, **Γ**, to the optimization cost function based on the distance between landmarks detected from nodes *i* and *j*, when there is some indication that they are the same landmark (*e.g.*, visual similarity). Ex1005, 1164, 1166; Ex1003, ¶317. If the cost of associating the landmarks is less than the penalty in the optimized graph, the algorithm determines that the landmarks (*i.e.*, determines that both are the home locator), and modifies the graph accordingly. Ex1005, 1164; Ex1003, ¶¶317–18.

n. Claim 6

Stachniss discloses this limitation. Ex1003, ¶¶320–23. For example, Stachniss discloses that, "[i]n passive SLAM algorithms, some other entity [a user] controls the robot, and the SLAM algorithm is purely observing. The vast majority of algorithms are of this type; they give the robot designer the freedom to implement ***arbitrary motion controllers*** [a user interface for controlling the robot by at least one user], and pursue ***arbitrary motion objectives***." Ex1005, 1156; Ex1003, ¶¶321–22.

o. Element 7[a]

Stachniss discloses this limitation. Ex1003, ¶¶324–28. For example, Stachniss explains that "[t]he initial location x_0 [root node] often serves as a ***point of reference*** [reference location] for the estimation algorithm." Ex1005, 1154, 1162–63; Ex1003, ¶¶325–27.

p. Element 7[b]

Stachniss discloses this limitation. Ex1003, ¶¶329–33. As explained in IV.B.2.d, Stachniss discloses scan-matching based on feature detection in overlapping scans of an environment. Ex1005, 1165–69; Ex1003, ¶330. Stachniss further discloses that scan-matching is performed throughout the graph, as "visual odometry," which estimates distance traveled between two poses by using sequential camera measurements taken from the camera mounted on the robot (scans take at least two of the respective nodes), for example by using a "***[f]airly standard*** combination of SURF matching and RANSAC" (finding overlap in measurements of distinct features). Ex1005, 1165, 1168, 1174; Ex1003, ¶331.

Stachniss further depicts detection of the same landmark from at least two nodes in several different groupings in Figure 46.7 (below), thereby disclosing scans taken at least two of the respective nodes of the plurality of nodes, the root node is different from the respective node. Ex1003, ¶331.

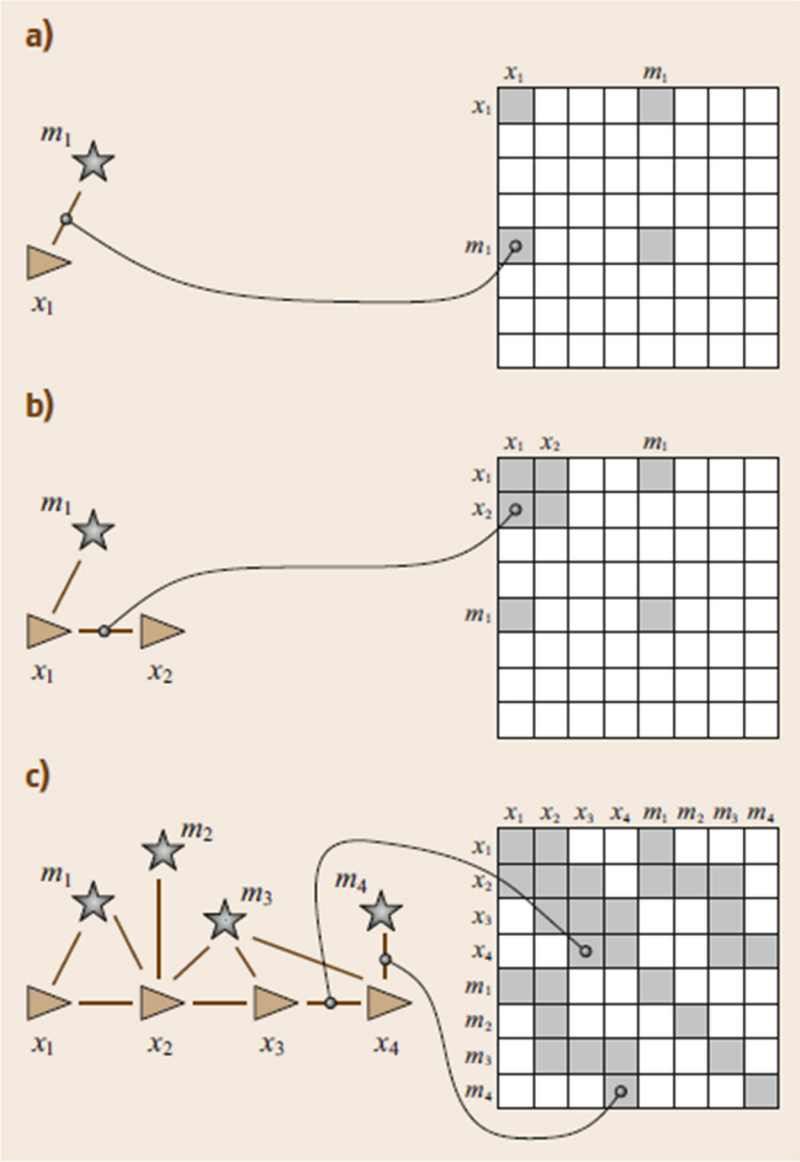


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

Stachniss further discloses hierarchical SLAM techniques which use "independent local maps, which are merged in case of re-visiting a place." Ex1005, 1164; *see also* § IV.B.2.d. A POSITA would have understood that an independent local map comprises more than one node, and therefore comprises at least two nodes different than the root node (initial location of the graph). Ex1003, ¶332.

q. Element 7[c]

Stachniss discloses this limitation. Ex1003, ¶¶334–37. For example, as explained in IV.B.2.d, p, Stachniss depicts poses x_2–x_4 (an extended scan group) grouped based on mutual detection of landmark m_3 (based at least in-part on overlapping distinct features of the scans at the at least two of the respective nodes) in Figure 46.7 (below). Ex1003, ¶335.

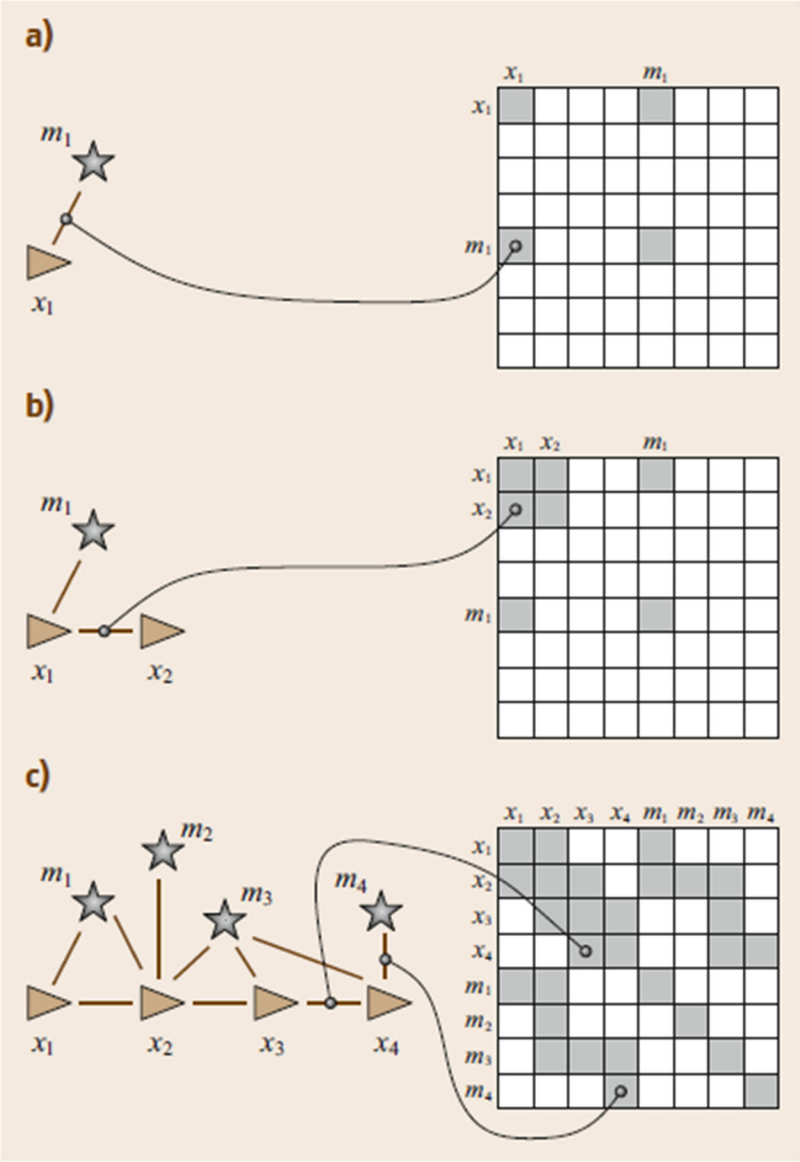


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

Further, as explained in IV.B.2.d, Stachniss discloses "Hierarchical SLAM," "a technique for using independent local maps, which are merged in case of re-visiting a place." Ex1005, 1164. Stachniss further discloses that these are advantageously employed in the context of "dense sensor[s]," like "Kinect cameras." Ex1005, 1164. Further, Stachniss explains that this approach "employs an incremental, lazy optimization scheme that allows for optimizing large graphs and at the same time can be executed at each step during mapping." Ex1005, 1164. A POSITA would have understood that disclosure of a hierarchical system capable of real-time optimization using feature-rich data like cameras discloses grouping of nodes into groups for stability and improved performance. Ex1003, ¶336.

r. Element 8[pre]

To the extent that the preamble is limiting, Stachniss discloses it. Ex1003, ¶¶338–43. Stachniss discloses a robot that maps its environment while it traverses that environment. Ex1005, 1153–54; Ex1003, ¶¶339–42. Stachniss explains that simultaneous localization and mapping (SLAM) is "one of key enabling technologies of robot navigation." Ex1005, 1153–54.

s. Element 8[a]

Stachniss discloses this limitation as discussed above in IV.B.2.c (Element 1(b); incorporated herein by reference). Ex1003, ¶¶344–45.

t. Element 8[b]

Stachniss discloses this limitation. Ex1003, ¶¶346–50. For example, Stachniss discloses a robot with "memory and computation power," capable of calculating and storing maps from sensor data as it moves through the environment based on instructions stored on that memory. Ex1005, 1153–54, 1157, 1164. Stachniss further discloses using a graphical processing unit which is a processor that allows for "dense processing methods" and allows for quick 3-D mapping. Ex1005, 1169. In addition, Stachniss describes robots processing information data, and further discloses several mathematical models that require a processor for the robot to compute while traveling in an environment. Ex1005, 1154–1155, 1157–62; Ex1003, ¶¶347–48. Stachniss also states that robots "process all data at the same time," and can perform "relative optimization . . . aim[ed] at computing locally consistent geometric maps," referring to a processor that executes computer readable instructions. Ex1005, 1155, 1164–65. Ex1003, ¶348. A POSITA would have understood that these disclosures disclose a mapping and localization unit capable of performing the claimed steps. Ex1003, ¶349.

u. Element 8[b][1]

Stachniss discloses this limitation as discussed above in IV.B.2.c (Element 1(b); incorporated herein by reference). Ex1003, ¶¶351–52.

v. Element 8[b][2]

Stachniss discloses this limitation as discussed above in IV.B.2.d (Element 1(c); incorporated herein by reference). Ex1003, ¶¶353–54.

w. Element 8[b][3]

Stachniss discloses this limitation as discussed above in IV.B.2.d (Element 1(c); incorporated herein by reference). Ex1003, ¶¶355–56.

x. Element 8[b][4]

Stachniss discloses this limitation as discussed above in IV.B.2.e (Element 1(d); incorporated herein by reference). Ex1003, ¶¶357–58.

y. Claim 9

Stachniss discloses this limitation as discussed above in IV.B.2.g (Element 2(b); incorporated herein by reference). Ex1003, ¶¶359–60.

z. Claim 10

Stachniss discloses this limitation as discussed above in IV.B.2.j–k (Claim 3; incorporated herein by reference). Ex1003, ¶¶361–62.

aa. Claim 11

Stachniss discloses this limitation as discussed above in IV.B.2.i (Element 2(d); incorporated herein by reference). Ex1003, ¶¶363–64.

bb. Claim 12

Stachniss discloses this limitation as discussed above in IV.B.2.b (Element 1(a); incorporated herein by reference). Ex1003, ¶¶365–66.

cc. Claim 13

Stachniss discloses this limitation. Ex1003, ¶¶367–69. As explained in IV.B.2.n, Stachniss discloses a robot navigating under the control of a user. A POSITA would have understood that disclosure of a robot navigating under the control of a user also discloses a means for controlling the robot (a user interface). Ex1003, ¶368.

dd. Claim 14

Stachniss discloses this limitation. Ex1003, ¶¶370–73. For example, Stachniss compares passive SLAM algorithms, as in IV.B.n, cc, with active SLAM algorithms, where "the robot actively explores [navigates the robot autonomously without the user] its environment in pursuit of an accurate map." Ex1005, 1156; Ex1003, ¶372.

ee. Element 15[pre]

Stachniss discloses this limitation. Ex1003, ¶¶374–78. For example, Stachniss discloses a robot with "memory and computation power," capable of calculating and storing maps from sensor data as it moves through the environment

based on instructions stored on that memory. Ex1005, 1153–54, 1157, 1164; Ex1003, ¶375. Stachniss further discloses using a graphical processing unit which is a processor that allows for "dense processing methods" and allows for quick 3-D mapping. Ex1005, 1169; Ex1003, ¶375. In addition, Stachniss describes robots processing information data, and further discloses several mathematical models that require a processor for the robot to compute while traveling in an environment. Ex1005, 1154–1155, 1157–62; Ex1003, ¶375. Stachniss also states that robots "process all data at the same time," and can perform "relative optimization . . . aim[ed] at computing locally consistent geometric maps," referring to a processor that executes computer readable instructions. Ex1005, 1155, 1164–65. Ex1003, ¶376. A POSITA would have understood that such a robot meets this limitation. Ex1003, ¶377.

ff. Element 15[a]

Stachniss discloses this limitation. Ex1003, ¶¶379–81. As explained in IV.B.2.c, Stachniss discloses a respective node of the plurality of nodes corresponds to (being associated with) a scan generated by a sensor of the robot at a location in the environment. A POSITA would have understood that a robot with a processor and memory (§ IV.B.2.t, ee, *supra*) configured to take scans at a plurality of nodes

transmits a signal to those sensors instructing the sensors to generate scans. Ex1003, ¶380.

gg. Element 15[b]

Stachniss discloses this limitation as discussed above in IV.B.2.u (Element 8(b)(1); incorporated herein by reference). Ex1003, ¶¶382–383.

hh. Element 15[c]

Stachniss discloses this limitation as discussed above in IV.B.2.d, v (Elements 1(c) and 8(b)(2); incorporated herein by reference). Ex1003, ¶¶384–385.

ii. Element 15[d]

Stachniss discloses this limitation as discussed above in IV.B.2.d, w (Elements 1(c) and 8(b)(3); incorporated herein by reference). Ex1003, ¶¶386–87.

jj. Element 15[e]

Stachniss discloses this limitation as discussed above in IV.B.2.e, x (Elements 1(d) and 8(b)(4); incorporated herein by reference). Ex1003, ¶¶388–89.

kk. Claim 16

Stachniss discloses this limitation. Ex1003, ¶¶390–93. As explained in IV.B.2.d, Stachniss discloses "independent local maps" (extended scan groups) based on detection of overlapping features within the group, with scans associated with each node. Ex1005, 1164.

Stachniss further discloses each extended scan group includes at least three or more scans. For example, Stachniss depicts a simplified pose-landmark graph wherein the extended scan group consists of pose-nodes x_2–x_4, and each pose-node comprises a scan of landmark m_3 (at least three or more scans) in Figure 46.7 (below). Ex1005, 1163; Ex1003, ¶392.

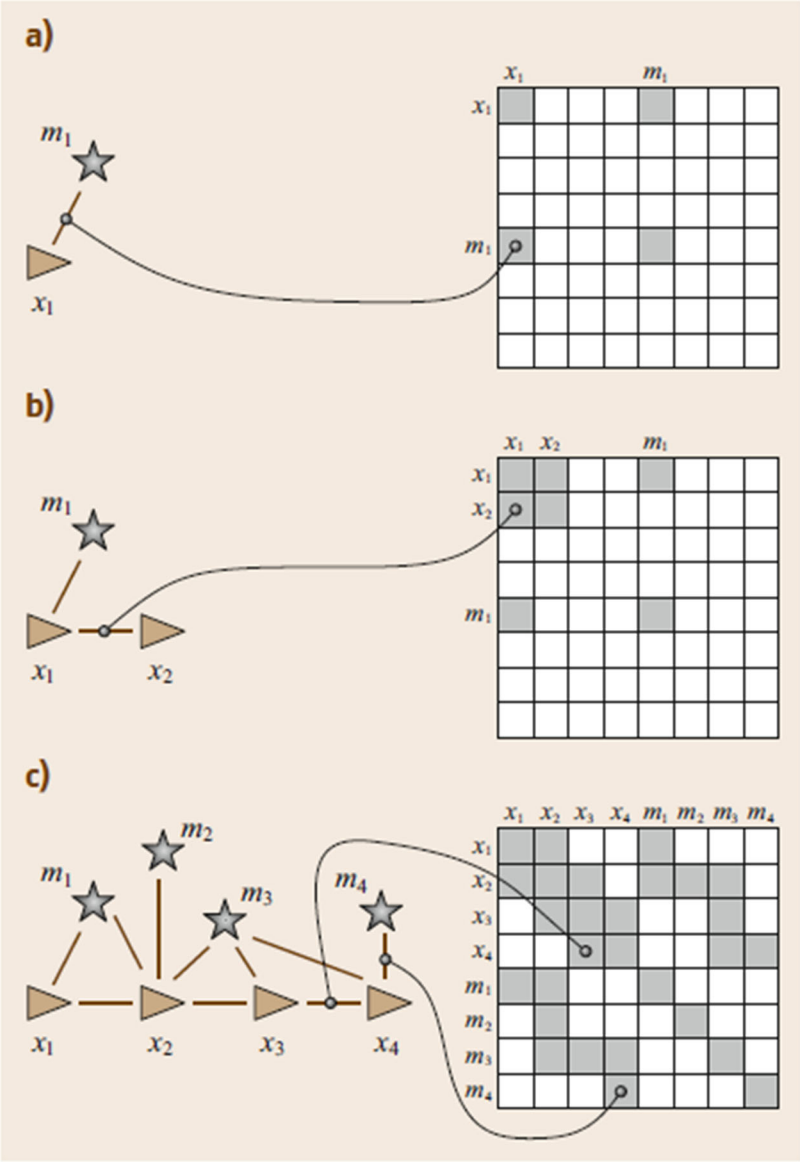


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation ls landmark m_1. (b) Robot motion from x_1 to x_2. (c) Several steps later

Ex1005, Fig. 46.7.

ll. Claim 17

Stachniss discloses this limitation as discussed above in IV.B.2.j, z (Element 3(a) and Claim 10; incorporated herein by reference). Ex1003, ¶¶394–95.

mm. Claim 18

Stachniss discloses this limitation as discussed above in IV.B.2.k, z (Element 3(b) and Claim 10; incorporated herein by reference). Ex1003, ¶¶396–97.

C. Grounds 4 and 5: Obviousness in view of Olson or Stachniss in combination with Fong

To the extent the limitations of claims 1–18 are not anticipated by Olson or Stachniss, it would have been obvious to modify either of those references in view of Fong to render each claim of the '325 Patent obvious.

1. Overview of Fong

Fong discloses an autonomous robot which uses "pose-defining fiducial markers" associated with its base station to assist in mapping its environment and navigating to the base station. Ex1006, 1:26–55. It depicts the base station with fiducial markers in Figure 4D (below).

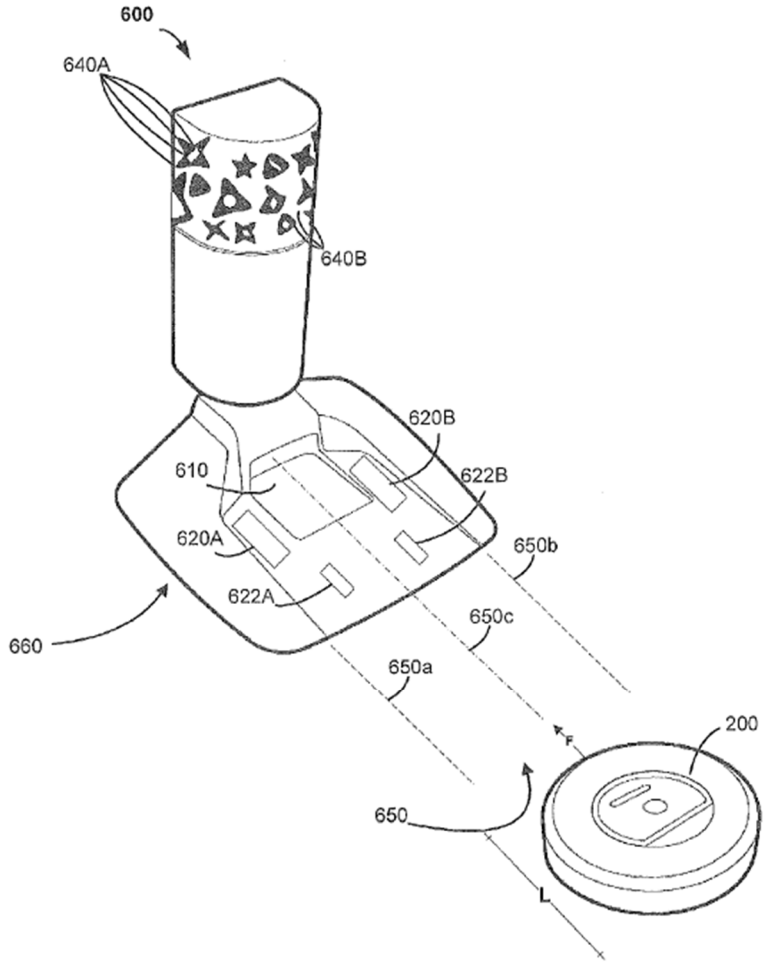


Fig. 4D

Ex1006, Fig. 4D.

Fong explains that its robot includes various systems and modules, including a "mapping/navigation system [that] can be used by the mobile robot 200 to map the enclosure space 20 and to determine or register the position of the robot 200 relative to the space 20." Ex1006, 6:26–29. The navigation system relies on "pose sensors,"

which Fong explains may include, without limitation, a camera. Ex1006, 6:20–25. The robot also includes a controller, with a processor and memory, that may control the mapping/navigation system. Ex1006, 5:9–36. Fong further explains that its robot may include a "service operation system," which may be "an onboard vacuum generator to vacuum clean the floor," or "a sweeping or mopping mechanism." Ex1006, 6:45–56. The robot and its subsystems are depicted in Figure 3 (below).

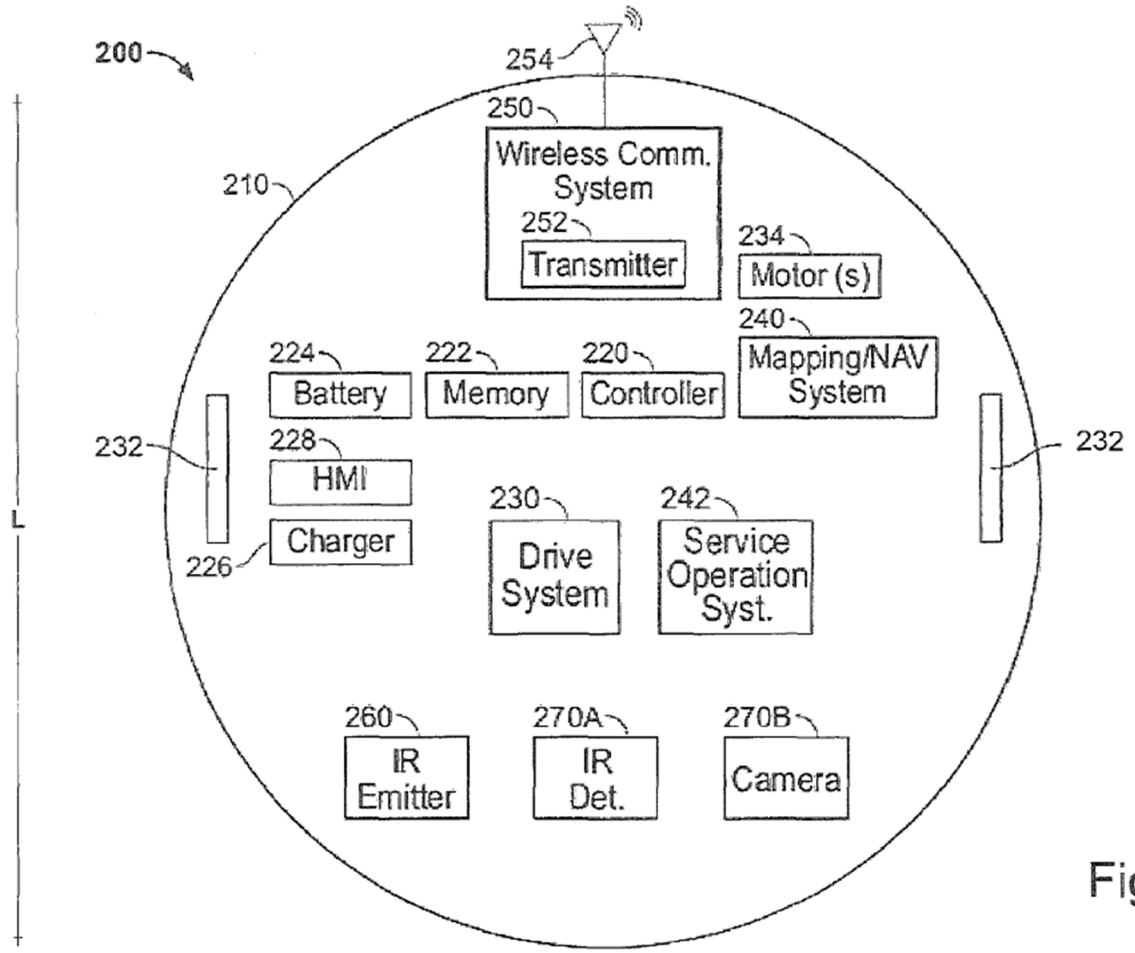


Fig. 3

Ex1006, Fig. 3.

a. Motivation to Combine Olson and Fong

A POSITA reviewing Olson or Stachniss would have been motivated to combine their teachings with the autonomous cleaning robot of Fong, including general robot features such as the memory and processor disclosed by Fong and specific features such as cleaning functions like vacuum of Fong. Ex1003, ¶399. Fong expressly teaches that its floor cleaner uses sensor data to generate a map and then relies on that map to plan a route, e.g., to a docking station. Ex1006, 6:26–36, 7:31–60. Fong further explains that it may use any suitable mapping and localization method, including SLAM techniques. Ex1006, 8:24–40.

Olson expressly teaches that it may be advantageously combined with any autonomous or semi-autonomous robot that generates and relies on maps, such as the robot disclosed in Fong. Ex1004, 9; Ex1003, ¶400. Similarly, Stachniss is a reference guide describing the overview of many topics in the robotics field. Ex1003, ¶400. It was designed to explain to POSITAs and layman various aspects of robotics, including simultaneous localization and mapping, to which Fong expressly directs itself. Ex1003, ¶400; Ex1006, 8:24–40. These combinations would have been obvious to a POSITA. Ex1003, ¶399.

A POSITA would have had a reasonable expectation of success in combining the autonomous cleaning robot of Fong with the mapping technologies described in Olson and Stachniss. Ex1003, ¶400. Olson explains that its method is suitable for combination with robots using different sensors, including cameras and laser scanners, and even mentions Roomba, a vacuum cleaner. Ex1004, 9, 109–122; Ex1003, ¶400. Likewise, Stachniss is intended as a "comprehensive introduction" to autonomous mapping and navigation with sensors, and it provides various methods to implement such a function. Ex1005, 1153; Ex1003, ¶400. Fong discloses that its robot uses sensors, and further non-exhaustively discloses that it may use a camera. Ex1006, 6:20–25. A POSITA would have therefore had a reasonable expectation of success in applying the methods disclosed in Olson or Stachniss in place of the generic SLAM method described in Fong. Ex1003, ¶400.

2. Detailed Analysis of Ground 3

As explained below and in further detail in the Declaration of Dr. Karam, all elements of claims 1–18 of the '325 Patent are obvious in view of Olson in combination with Fong.

b. Claim 5

To the extent that Olson or Stachniss do not anticipate, the Olson/Fong and Stachniss/Fong combinations disclose this limitation. Ex1003, ¶¶402–06. Fong

discloses that, upon sensing the fiducial markers (home locators), the robot may "determine real or near-real time coordinates of the robot with respect to the pose of the dock 600." Ex1006, 13:38–42. Defining the position of the robot in relationship to the detected start position applies a constraint to the robot's current position to assist in localization and reduce the error associated with its position. Ex1003, ¶¶403–04. Accordingly, detection of these fiducial markers also allow the robot to determine when it has arrived at the docking station (start and end positions in view of a home locator). Ex1006, 4:45–5:8, 6:64–7:6; Ex1003, ¶¶403–04.

It would have been obvious to a POSITA to include this element, such as the one disclosed in Fong, with the systems disclosed in Olson/Stachniss. Ex1003, ¶405. Specifically, a POSITA would have known that it would have been be beneficial for the robot to determine that it has returned to the start location, for example, so that it can begin a mode of operation associated with charging. Ex1003, ¶405. A POSITA would have a reasonable expectation of success in adding this functionality, because Olson/Stachniss provide a method for the robot to determine its position with reference to the robot's prior motion and landmarks in the environment at any location, especially the visually distinct start location described in Fong. Ex1003, ¶405.

c. Element 8[b]

To the extent that Olson or Stachniss do not anticipate, the Olson/Fong and Stachniss/Fong combinations disclose this limitation. Ex1003, ¶¶407–11. For example, Fong discloses that its "mobile robot **200** includes . . . a mapping/navigation system [mapping and localization unit] **240**." Ex1006, 5:12–19; Ex1003, ¶408. Fong further discloses that the "controller **220** may be configured to . . . control a mapping function of the mapping/navigation system **240**." Ex1006, 5:26–36. Fong further discloses that the "mapping/navigation system **240** can be used by the mobile robot **200** to map the enclosure space **20** and to determine or register the position of the robot **200** relative to the space **20**." Ex1006, 6:26–29. Fong further discloses that the "data from the directional sensors may be combined with an analysis of the robot's current pose on a map that the mapping and navigation system **240** is building, for example using Simultaneous Localization and Mapping (SLAM) techniques." Ex1006, 8:28–32. Fong depicts the mapping and localization unit in Figure 3 (below).

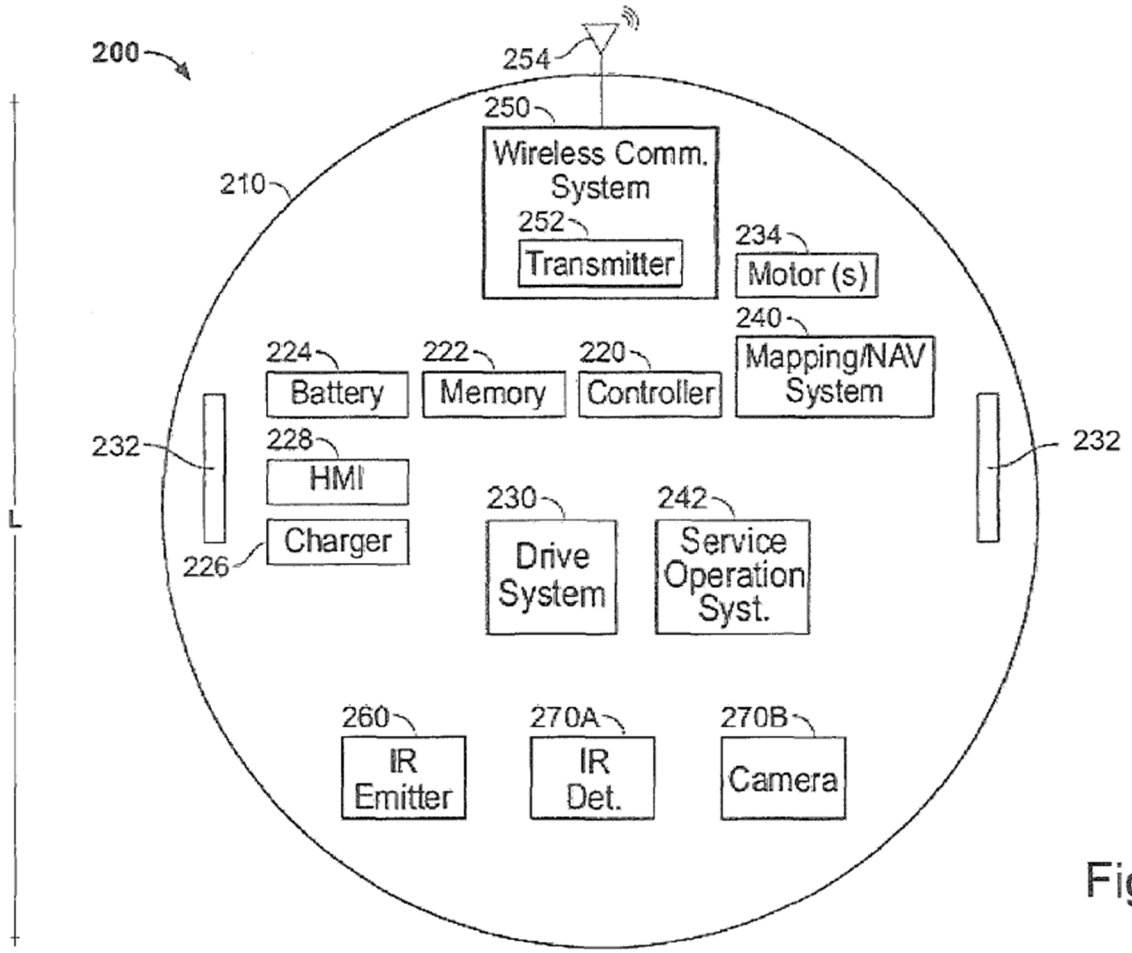


Fig. 3

Ex1006, Fig. 3.

It would have been obvious to a POSITA to include this element, such as the one disclosed in Fong, with the systems disclosed in Olson/Stachniss. Ex1003, ¶410. Specifically, a POSITA would have known that it would have been common for the robot to have a system dedicated to performing the mapping and localization functions described in Olson/Stachniss. Ex1003, ¶410. A POSITA would have had

a reasonable expectation of success in adding this feature to its system, as such units are typical, and it would have therefore been a simple addition. Ex1003, ¶410.

d. Claim 13

To the extent that Olson or Stachniss do not anticipate, the Olson/Fong and Stachniss/Fong combinations disclose this limitation. Ex1003, ¶¶412–18. For example, Fong discloses that the "robot **200** includes a chassis **210**, a controller **220**, . . . [and] a human-machine interface (HMI) [user interface] **228**." Ex1006, 5:12–19, Figure 3 (below); Ex1003, ¶¶413–14.

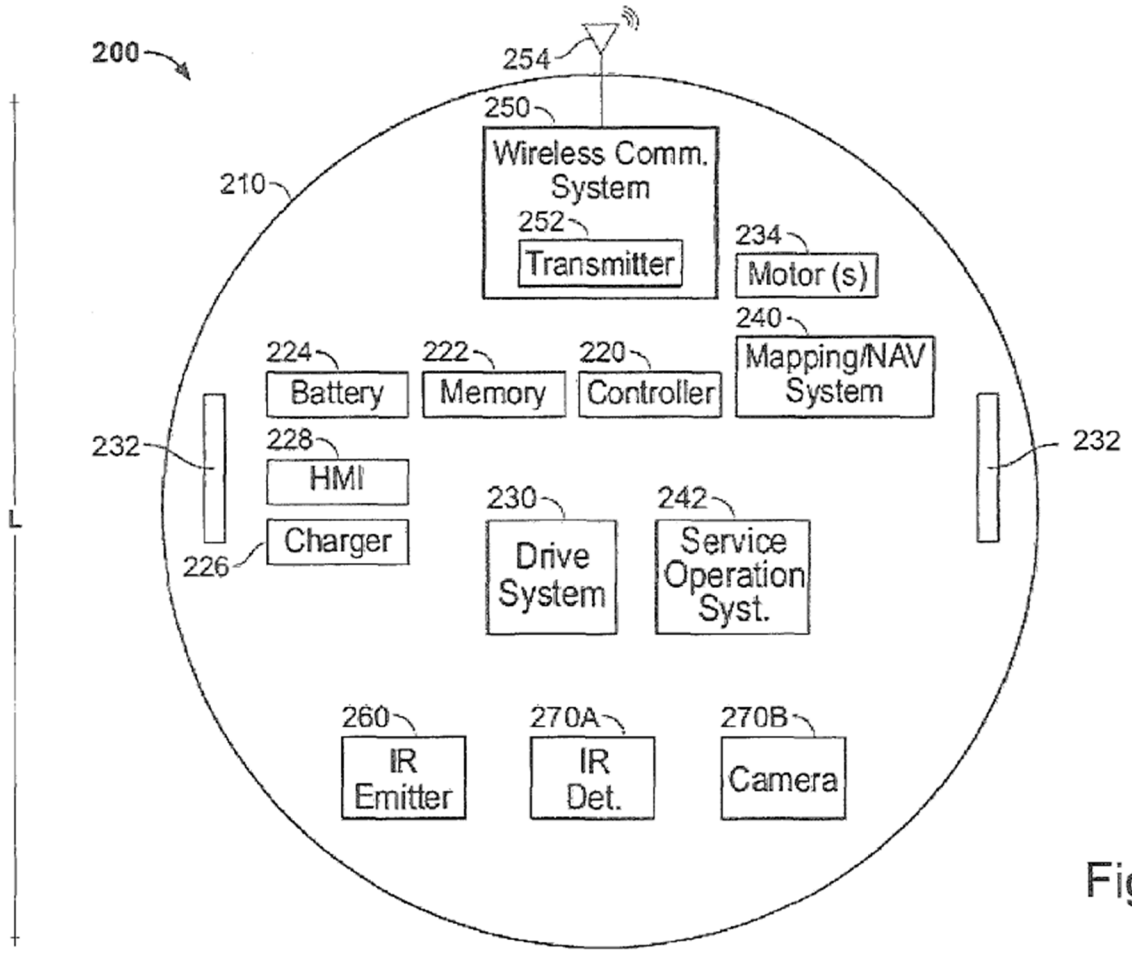


Fig. 3

Ex1006, Fig. 3.

As a further example, Fong discloses that "some or all of the operations of the controller **220** may be performed by the **600** or by other processors, such as . . . the local user terminal **142** and/or the remote user terminal **144**." Ex1006, 7:7–17; *see also* Ex1006, 3:64–4:19; 6:37–64; 12:66–13:6. A POSITA would have understood that local and remote user terminals are user interfaces for controlling the robot by

at least one user. Ex1003, ¶¶415–16. Fong depicts the relationship of these user interfaces with its robot in Figure 1 (below). *See also* Ex1006, Figure 4A.

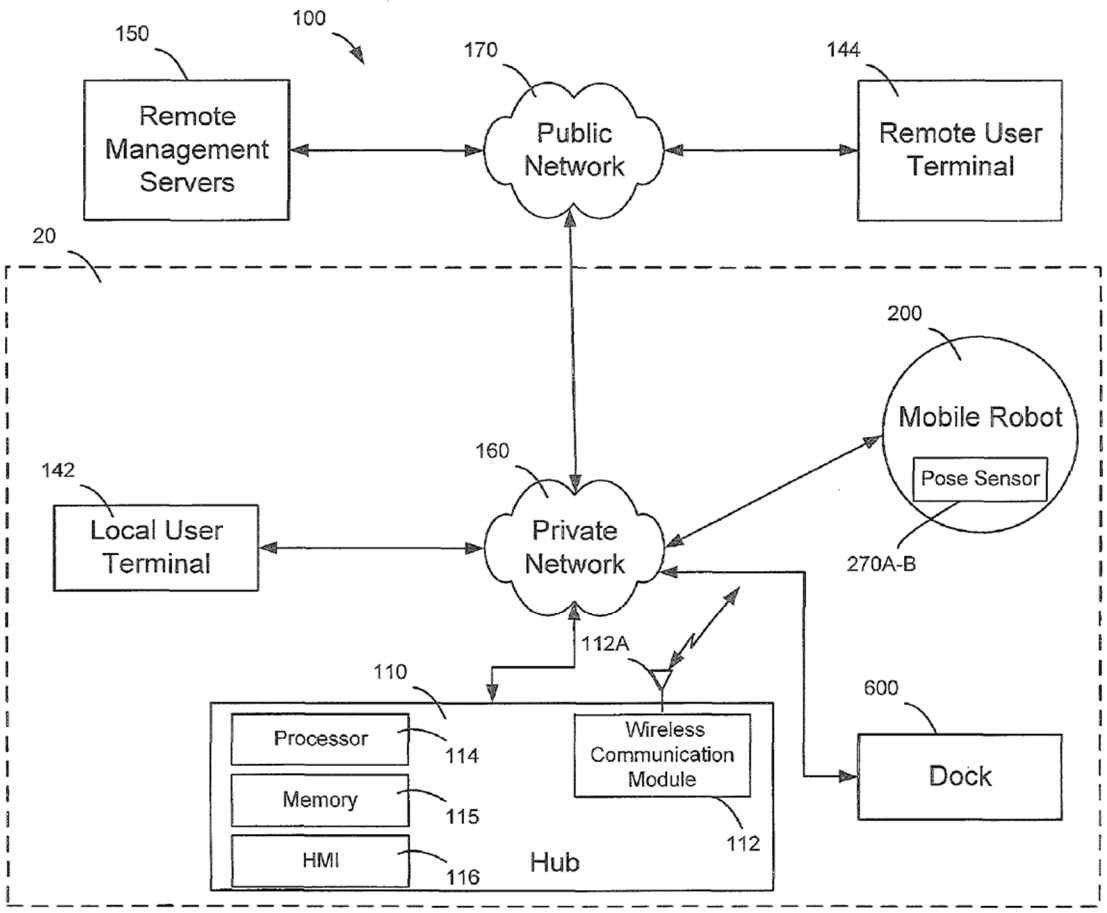


Fig. 1

Ex1006, Figure 1.

It would have been obvious to a POSITA to include a user interface, such as the one disclosed in Fong, with the systems disclosed in Olson/Stachniss. Ex1003, ¶417. Specifically, a POSITA would have known that it would be advantageous to provide a means to a user to control the robots disclosed in Olson/Stachniss.

Ex1003, ¶417. A POSITA would have had a reasonable expectation of success in making these combinations, as the POSITA would have known that robots often include user interfaces to enable user control and that this addition would have therefore been simple. Ex1003, ¶417.

e. Element 15[pre]

To the extent that Olson or Stachniss do not anticipate, the Olson/Fong and Stachniss/Fong combinations disclose this element. Ex1003, ¶¶419–423. Fong discloses a robot that contains a memory, such as "a portable computer diskette, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory) and a portable compact disc read-only memory (CD-ROM)." Ex1006, 2:52–3:3. The memory stores computer readable instructions. Ex1006, 2:35–42; Ex1003, ¶¶420–21.

It would have been obvious to a POSITA to include a memory, such as the one disclosed in Fong, with the systems disclosed in Olson/Stachniss. Ex1003, ¶422. Specifically, robots generally contain a memory to store the data that they receive from the sensors and to perform the calculations necessary to render the map. Ex1003, ¶422. In fact, the addition of a memory in robots is standard practice and a POSITA would have had a reasonable expectation of success in making this simple addition. Ex1003, ¶422.

D. Grounds 5 and 6: Obviousness in view of Olson and Stachniss in combination with Schnittman

To the extent the limitations of claims 1–18 are not anticipated by Olson or Stachniss, it would have been obvious to modify either of those references in view of Schnittman to render each claim of the '325 Patent obvious.

1. Overview of Ground and Prior Art

Schnittman discloses a mobile robot configured to autonomously map and navigate an environment using a method that implements ray-tracing. Schnittman explains that he employs a SLAM algorithm which generates a "particle map," and that "[u]pdating the particle map may include executing a ray trace of the accumulated synchronized sensor data and applying a range sensor model to the accumulated synchronized sensor data." Ex1007, 2:29–32. Schnittman depicts the role of ray tracing in its mapping algorithm in Figure 11 (below).

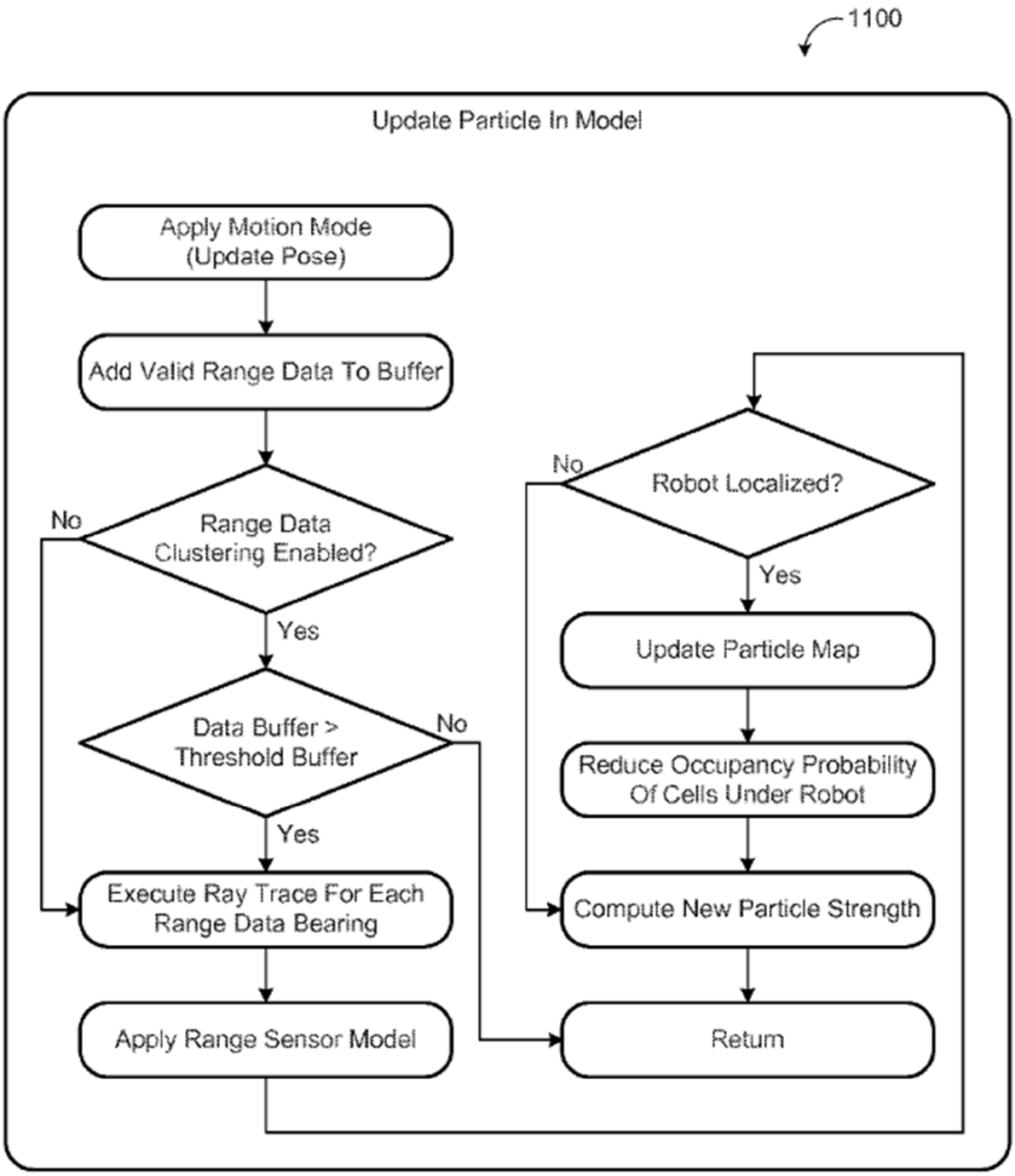

1100
Update Particle In Model
Apply Motion Mode (Update Pose)
Add Valid Range Data To Buffer
Range Data Clustering Enabled?
No
Yes
Data Buffer > Threshold Buffer
No
Yes
Execute Ray Trace For Each Range Data Bearing
Apply Range Sensor Model
Robot Localized?
No
Yes
Update Particle Map
Reduce Occupancy Probability Of Cells Under Robot
Compute New Particle Strength
Return

FIG. 11

Ex1007, Figure 11.

a. Motivation to Combine Stachniss and Schnittman

A POSITA reviewing Olson or Stachniss would have been motivated to combine their teachings with the autonomous cleaning robot of Schnittman, including ray tracing as disclosed by Schnittman. Ex1003, ¶¶425–426. Schnittman expressly teaches that its robot uses sensor data to generate a map and then relies on that map to navigate. Ex1007, 1:34–53; 7:33–53; Ex1003, ¶425. Schnittman further explains that its method relates to particle-based SLAM methods, which allow the map to be updated by updating particle weights. Ex1007, 1:34–2:56; Ex1003, ¶425. Further, Schnittman explains that its capacity to update maps enables autonomous navigation. Ex1007, 9:3–21, 11:4–9. Stachniss explains that graph-based methods are capable of building large maps, but require special handling when "revisit[ing] already mapped terrain." Ex1005, 1165–66. Accordingly, a POSITA would have been motivated to combine the particle update method based on ray tracing disclosed in Schnittman with the graph-based SLAM methods disclosed in Olson and Stachniss. Ex1003, ¶425.

A POSITA would have had a reasonable expectation of success in combining the autonomous robot of Schnittman with the mapping technologies described in Olson and Stachniss. Ex1003, ¶426. Olson expressly teaches that it may be

advantageously combined with any autonomous or semi-autonomous robot that generates and relies on maps, such as the robot disclosed in Schnittman. Ex1004, 9; Ex1003, ¶426. Similarly, Stachniss is a reference guide describing the overview of many topics in the robotics field. Ex1005, 1153; Ex1003, ¶426. It was designed to explain to POSITAs and layman various aspects of robotics, including simultaneous localization and mapping, to which Schnittman expressly directs itself. Ex1003, ¶426; Ex1007, 5:54–59. A POSITA would have therefore had a reasonable expectation of success in applying the methods disclosed in Olson or Stachniss in combination with the SLAM method described in Schnittman. Ex1003, ¶426.

2. Detailed Analysis of Grounds 4 and 5

As explained below and in further detail in the Declaration of Dr. Karam, all elements of claims 1–18 of the '325 Patent are obvious in view of Olson or Stachniss in combination with Schnittman.

a. Element 2[d]

Schnittman discloses this element. Ex1003, ¶¶427–32. For example, Schnittman discloses that "[u]pdating the particle map [generating the map] may include ***executing a ray trace*** of the accumulated synchronized sensor data and applying a range sensor model to the accumulated synchronized sensor data [scans generated by the sensor]." Ex1007, 2:24–34, 4:50–53, 17:1–26; Ex1003, ¶428.

Schnittman explains that "[e]xecuting the ray trace may include, for each range measurement and bearing pair, receiving the bearing and an existing particle map and computing a predicted ranged. The method may further include receiving a measured range, receiving the predicted range, and computing a probability of occupancy of an object in each cell of the particle map ***along the ray trace***." Ex1007, 2:35–43, 3:56–64, 4:2–10, 22:42–45. Schnittman depicts the role of the ray trace in its mapping algorithm in Figure 11 (below).

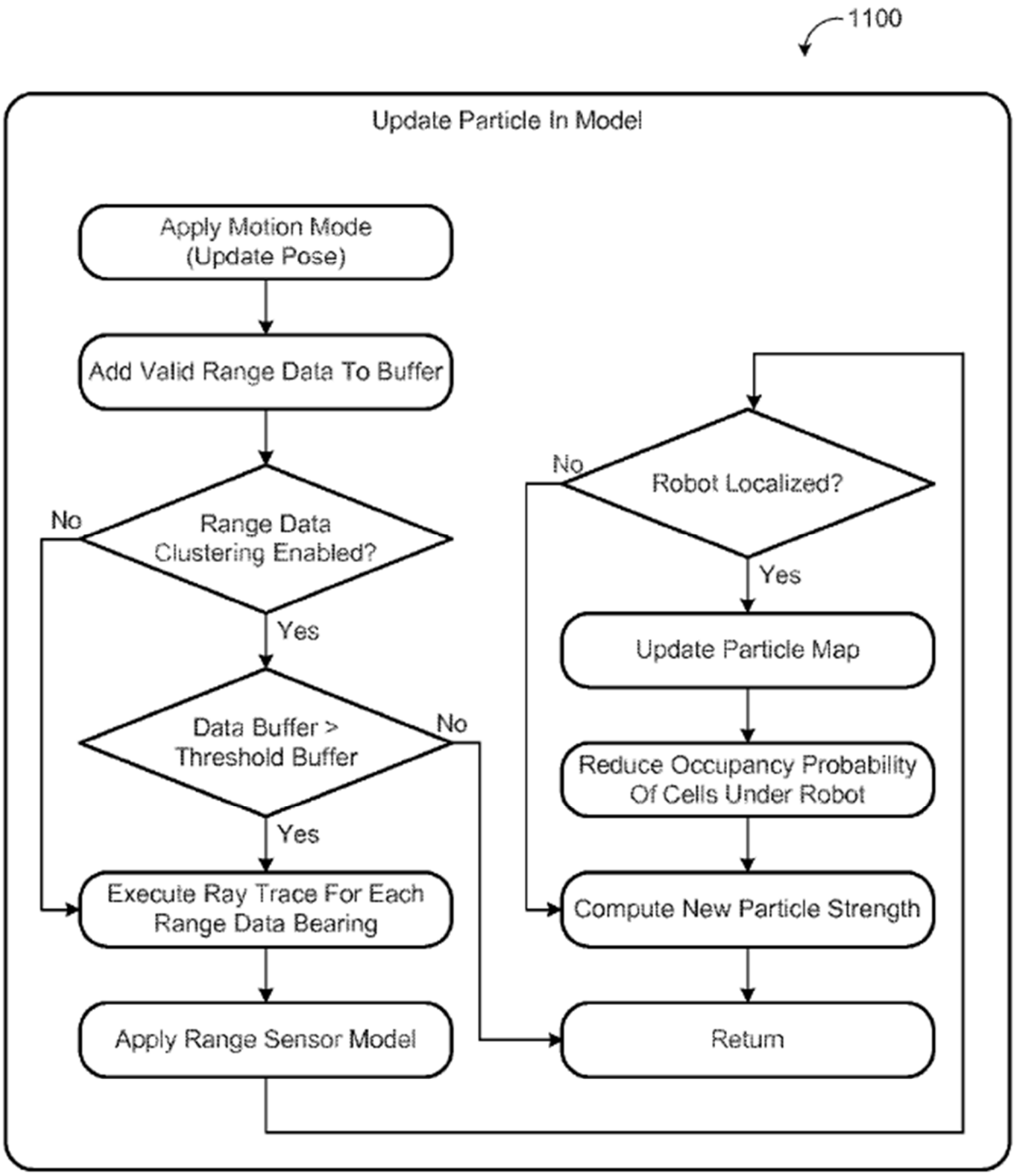

1100
Update Particle In Model
Apply Motion Mode (Update Pose)
Add Valid Range Data To Buffer
Range Data Clustering Enabled?
No
Yes
Data Buffer > Threshold Buffer
No
Yes
Execute Ray Trace For Each Range Data Bearing
Apply Range Sensor Model
Robot Localized?
No
Yes
Update Particle Map
Reduce Occupancy Probability Of Cells Under Robot
Compute New Particle Strength
Return

FIG. 11

Ex1007, Figure 11.

A POSITA would have been motivated to combine the ray-tracing procedure disclosed in Schnittman with the algorithms of Olson and Stachniss, at least because Schnittman explains that ray-tracing permits efficient updated maps during navigation, allowing the robot to respond to a dynamic environment, for example to avoid obstacles. Ex1007, 9:3–21; Ex1003, ¶431. A POSITA would have had a reasonable expectation of success, as Schnittman explains that its method, like those in Olson and Stachniss, is a SLAM method using sensors and SLAM controllers. Ex1007, 5:54–59, 9:3–21, 10:59–11:3; Ex1003, ¶431.

b. Claim 11

The Olson/Schnittman and Stachniss/Schnittman combinations disclose this limitation, as discussed above in IV.D.2.a (Element 2(d); incorporated herein by reference). Ex1003, ¶¶433–434.

V. ENABLEMENT AND SECONDARY CONSIDERATIONS

The prior art references relied upon in this Petition are enabled.

In parallel litigation, the Patent Owner has asserted that this patent (along with four other patents asserted) generally solve a long-felt need, in allowing it to become an industry leader in autonomous robots and artificial intelligence. It identified a number of awards and recognition in the industry. It also alleges that its products

have achieved commercial success and industry recognition given the number of robots it has sold and the hours of operation of those robots. Further, it alleges that Petitioner has willfully infringed the asserted patents and copied Patent Owner's technology. Ex1022, 11–14. Petitioner denies that it has infringed the asserted patents or that it copied Patent Owner's technology.

Moreover, Patent Owner's vague allegations on long-felt need, commercial success, industry recognition, and copying are untethered to the specific claims at issue in the Challenged Patent. Patent Owner establishes no nexus between the claims and any of the alleged secondary indicia of non-obviousness. Thus, Petitioners disagree that these are evidence of secondary considerations of non-obviousness tied to the Challenged Claims. Ex1003, ¶¶435–37. To the extent Patent Owner alleges that any secondary considerations of non-obviousness are tied to the Challenged Claims, Petitioners may address such allegations in its reply. In any event, where, as here, there is a strong showing of obviousness, the Federal Circuit has held that even relevant secondary considerations supported by substantial evidence do not dislodge the primary conclusion of obviousness. *Ohio Willow Wood Co. v. Alps S., LLC*, 735 F.3d 1333, 1344 (Fed. Cir. 2013).

VI. CONCLUSION

Petitioners have established a reasonable likelihood that the Challenged Claims are unpatentable. Petitioners therefore respectfully request that IPR be instituted and that all Challenged Claims be found unpatentable.

DATED: December 4, 2024

Respectfully Submitted,

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CERTIFICATION UNDER 37 C.F.R. § 42.24(d)

Under the provisions of 37 C.F.R. § 42.24(d), the undersigned attorney hereby certifies that the word count for Sections I–VII of the foregoing Petition for *Inter Partes* Review is 13,638 according to the word count tool in Microsoft Word.

DATED: December 4, 2024

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CERTIFICATE OF SERVICE

The undersigned certifies service pursuant to 37 C.F.R. §§ 42.6(e) and 42.105(a), (b) on the Patent Owner via FedEx overnight mail of a copy of this Petition for *Inter Partes* Review and supporting materials at the Patent Owner at the correspondence address of record for the '325 Patent:

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APPENDIX: CHALLENGED CLAIM LISTING

No.	Limitation
1[pre]	A method of generating a map by a robot, comprising:
1[a]	traveling, by the robot, in an environment;
1[b]	generating a graph comprising a plurality of nodes, a respective node of the plurality of nodes corresponds to a scan generated by a sensor of the robot at a location in the environment;
1[c]	performing scan matching on extended scan groups, the extended scan groups being determined in-part on at least two or more nodes of the plurality of nodes; and
1[d]	constraining the graph between a start location and an end location, the start location and the end location being at a substantially similar location in the environment.
2[a]	The method of claim 1, further comprising: associating a range of possible locations in the environment with the respective one of the plurality of nodes based at least in-part on the scan matching;
2[b]	determining confidences associated with a respective one of the range of possible locations;
2[c]	optimizing the graph to find a location of the plurality of nodes based at least in-part on the confidences; and
2[d]	generating the map from the optimized graph, the generation of the map comprises ray tracing with the scans generated by the sensor, the scans being associated with the plurality of nodes.
3[a]	The method of claim 2, wherein the optimizing of the graph, comprises: generating a cost function based at least in-part on: (1) relative locations of each of the plurality of nodes, and (2) the confidences associated with each of the plurality of nodes; and
3[b]	solving the cost function for a minimum value.
4	The method of claim 2, wherein the associated confidences further includes, using a probability distribution indicative at least in-part of a probability that the respective node is in a respective location.

No.	Limitation
5	The method of claim 1, wherein the constraining of the graph to the start and end locations includes constraining the graph to the start and end locations in view of a home locator.
6	The method of claim 1, wherein the traveling, by the robot, in the environment further includes, navigating the robot under user control.
7[a]	The method of claim 1, wherein the extended scan groups determined at least in part from groups of the plurality of nodes, further includes, selecting a root node as a reference location;
7[b]	finding overlap in measurements of distinct features in scans taken at least two of the respective nodes of the plurality of nodes, the root note is different from the respective node; and
7[c]	grouping the the [sic] at least two of the respective nodes into extended scan groups based at least in-part on overlapping distinct features of the scans at the at least two of the respective nodes.
8[pre]	A robot, comprising:
8[a]	a sensor configured to generate scans of an environment at a plurality of nodes, a respective node of the plurality of nodes is associated with a location in the environment; and
8[b]	a mapping and localization unit configured to execute computer readable instructions to:
8[b][1]	generate a graph of the plurality of nodes based at least in part on the generated scans;
8[b][2]	determine extended scan groups in-part on at least two or more nodes of the plurality of nodes;
8[b][3]	perform scan matching on the extended scan groups; and
8[b]4]	constrain the graph between a start location and an end location, the start location and the end location being at a substantially similar location in the environment.

No.	Limitation
9	The robot of claim 8, wherein the mapping and localization unit is further configured to execute computer readable instructions to, determine confidences associated with the location in the environment of each node of the plurality of nodes.
10	The robot of claim 9, wherein the mapping and localization unit is further configured to execute computer readable instructions to, generate a cost function based at least in-part on the confidences and the location of each node of the plurality of nodes, the location of each node in the graph being determined based on solving the cost function for a minimum value.
11	The robot of claim 8, wherein the mapping and localization unit is further configured to execute computer readable instructions to, render a map from the graph, the map based at least in-part on ray tracings of the scans.
12	The robot of claim 8, further comprising: an actuator configured to move the robot between locations in the environment.
13	The robot of claim 8, further comprising: a user interface for controlling the robot by at least one user.
14	The robot of claim 8, further comprising: a navigation unit configured to navigate the robot autonomously without the user.
15[pre]	A non-transitory computer-readable medium having computer readable instructions stored thereon, that when executed by at least one processor, configure the at least one processor to:
15[a]	transmit a signal to at least one sensor to generate scans of an environment at a plurality of nodes, a respective node of the plurality of nodes being associated with a location in the environment;
15[b]	generate a graph of the plurality of nodes based in-part on the generated scans;
15[c]	determine extended scan groups based at least in part on two or more nodes of the plurality of nodes;
15[d]	perform scan matching on the extended scan groups; and

No.	Limitation
15[e]	constrain the graph between a start location and an end location, the start location and the end location being at a substantially similar location.
16	The non-transitory computer-readable medium of claim 15, wherein each extended scan group includes at least three or more scans.
17	The non-transitory computer-readable medium of claim 15, wherein the at least one processor is further configured to execute the computer readable instructions to, determine a cost function based at least in-part on confidences associated with the location of each node of the plurality of nodes.
18	The non-transitory computer-readable medium of claim 17, wherein the at least one processor is further configured to execute the computer readable instructions to, generate a map based at least in-part on minimizing the cost function.