

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

**DECLARATION OF LINA J. KARAM, PH.D.
IN SUPPORT OF PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 10,274,325**

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I, Dr. Lina J. Karam, Ph.D., do hereby declare as follows.

I. INTRODUCTION

1. I am making this declaration at the request of Avidbots Corp. and Avidbots USA Corp., (Petitioners, collectively Avidbots) in the matter of the *Inter Partes* Review of U.S. Patent No. 10,274,325 (“the ’325 patent”).

2. I am being compensated for my work in this matter at my standard hourly rate. I am also being reimbursed for reasonable and customary expenses associated with my work and testimony in this proceeding. My compensation is not contingent on the outcome of this matter or the specifics of my testimony.

3. I have been asked to provide my opinions regarding whether the subject matter of claims 1–18 (“the Challenged Claims”) of the ’325 patent would have been obvious to a person having ordinary skill in the art (“POSITA”) at the time of the alleged invention, in light of the prior art. It is my opinion that the Challenged Claims would have been obvious to a POSITA.

4. In the preparation of this declaration, I have studied:

- Edwin B. Olson, “Robust and Efficient Robotic Mapping,” Massachusetts Institute of Technology (June 2008) (Ex1004, “Olson”).
- Stachniss et al., Springer Handbook of Robotics, Chapter 46: Simultaneous Localization and Mapping, (Bruno Siciliano and Oussama Khatib eds., Springer 2nd ed., 2016) (Ex1005, “Stachniss”).

- U.S. Patent No. 9,538,892 (Ex1006, “Fong”).
- U.S. Patent No. 9,020,637 (Ex1007, Schnittman).

5. In forming the opinions expressed below, I have considered: the documents listed above; the relevant legal standards, including the standard for anticipation and the standard for obviousness; and my own knowledge and experience based upon my work in the field of autonomous systems and robotics, mapping and navigation, sensing, and signal processing, as described below, as well as portions of the following additional materials:

- Smith, Randall C., and Peter Cheeseman. “On the representation and estimation of spatial uncertainty.” *The International Journal of Robotics Research* 5.4 (1986): 56-68 (Ex 1009).
- Chatila, Raja, and Jean-Paul Laumond. “Position referencing and consistent world modeling for mobile robots.” *Proceedings of the 1985 IEEE International Conference on Robotics and Automation*. (1985):138-145 (Ex1010).
- Durrant-Whyte, Hugh, and Tim Bailey. “Simultaneous localization and mapping: part I.” *IEEE Robotics & Automation magazine* 13.2 (2006): 99-110 (Ex1011).
- Davison, Andrew J., and David W. Murray. “Mobile robot localisation using active vision.” *Proceedings of the 5th European Conference on*

- Computer Vision. Springer Lecture Notes in Computer Science (LNCS), Vol. 1407, Volume II (1998):809-825 (Ex1012).
- Lu, Feng, and Evangelos Milios. “Globally consistent range scan alignment for environment mapping.” *Autonomous Robots* 4 (1997): 333-349 (Ex1013).
 - Grisetti, Giorgio, et al. “A tutorial on graph-based SLAM.” *IEEE Intelligent Transportation Systems Magazine* 2.4 (2010): 31-43 (Ex1014).
 - 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 (Ex1015).
 - *Springer Handbook of Robotics*, Bruno Siciliano and Oussama Khatib eds., Springer 2nd ed., 2016 (Ex1016).
 - Macenski, Steve, and Ivona Jambrecic. "SLAM Toolbox: SLAM for the dynamic world." *Journal of Open Source Software* 6.61 (2021): 2783. 7 pages (Ex1017).
 - Giorgio Grisetti, Cyrill Stachniss, and Wolfram Burgard, *GMapping*, OpenSlam.org, <https://openslam-org.github.io/gmapping.html> (last visited Oct. 16, 2025) (Ex1018).
 - Grisetti, Giorgio, et al. “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):2432-2437 (Ex1019).
- Grisetti, Giorgio, et al. “Improved techniques for grid mapping with Rao-Blackwellized particle filters.” IEEE Transactions on Robotics 23.1 (2007):34-46 (Ex1020).
 - 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) (Ex1021).
 - Gutmann, Jens-Steffen, 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 (Ex1023).
6. Unless otherwise noted, all *emphasis* in any quoted material has been added.

II. BASIS FOR OPINIONS

A. Qualifications

7. In formulating my opinions, I have relied upon my knowledge, training, and experience in the relevant art. My qualifications are stated more fully in my curriculum vitae (CV), a copy of which can be found in Exhibit 1024. The following is a brief summary of my relevant qualifications and professional experience.

Among other things, my CV includes a list of my issued patents and publications for at least the last 30 years.

8. I earned a Bachelor of Engineering (B.E.) in Computer and Communications Engineering from the American University of Beirut in 1989, and a M.S. and a Ph.D. in Electrical Engineering both from the Georgia Institute of Technology in 1992 and 1995, respectively.

9. I am currently an Emerita Professor in the School of Electrical, Computer, and Energy Engineering at Arizona State University (ASU) and the Director of the R&D Image, Video, & Usability (IVU) Lab at ASU. Prior to becoming Emerita Professor, I was a tenured Full Professor, Computer Engineering Program Chair and Computer Engineering Director for Industry Engagement at ASU. From 2020 to 2022, I served as Dean of the School of Engineering at the Lebanese American University. From 2019 to 2021, I served as the Editor-In-Chief of the high-impact IEEE Journal of Special Topics in Signal Processing. I am also the President of PICARIS, LLC. I also served as Chief Technical Advisor at AIAEC LLC.

10. My research includes topics such as Signal, Image, and Video Processing, Compression, and Transmission; Computer Vision; Machine Learning; Autonomous Systems and Robotics; Perceptual-based Processing; Visual Attention Models; Automated Quality Assessment and Monitoring; Multidimensional Signal

Processing; and Digital Filter Design. I have various awards in recognition of my research, including U.S. National Science Foundation CAREER Award, Intel Outstanding Researcher Award, U.S. National Aeronautics and Space Administration (NASA) Technical Innovation Award, the IEEE Signal Processing Society (SPS) Best Journal Paper Award, and IEEE Phoenix Section Outstanding Faculty Award. I am featured in the 8th, 9th, 10th, and 11th editions of Research.com (2022-2025) among World Top Computer Science Scientists.

11. In addition, I am an Institute of Electrical and Electronics Engineers (IEEE) Fellow, which is the highest grade level conferred by IEEE each year to no more than one-tenth of 1% of all IEEE voting members. In addition to serving as Editor-In-Chief of a prestigious IEEE journal, I also served on several journal editorial boards, including but not limited to the IEEE Transactions on Image Processing, the IEEE Signal Processing Magazine, the IEEE Signal Processing Letters, and as Lead Guest Editor of the Proceedings of IEEE, Special Issue on Perceptual-Based Media Processing, IEEE Journal of Selected Topics in Signal Processing, Special Issue on Visual Quality Assessment, and IEEE Signal Processing Magazine, Special Issue on Autonomous Driving. I have also served on several IEEE Boards and chaired multiple IEEE committees. For example, I served on the IEEE Signal Processing Society (SPS) Board of Governors (2016-2018), IEEE SPS Publications Board (2019-2021), IEEE SPS Award Board (2019-2020),

IEEE SPS Conference Board (2003-2005 & 2017-2018), IEEE Publication Services and Products Board (PSPB) Strategic Planning Committee (2014-2016), IEEE Technical Activities Board (TAB)/PSPB Product and Services Committee (2023), IEEE Educational Activities Board (EAB) Faculty Resources Committee (2023-2024), IEEE SPS Fellow Nomination Committee (2025), IEEE Industry Engagement Committee and Chair of its Industry Impact Factor initiative (2024-present) and IEEE TechRxiv Advisory and Editorial Boards (2022-present). I am also an expert delegate of the ISO/IEC JTC1/SC29 Committee (Coding of audio, picture, multimedia, and hypermedia information) and have participated in JPEG/MPEG standardization activities.

12. As part of my various roles at ASU, PICARIS, AIAEC, ISO, and IEEE, I have been actively involved with industry. For example, I contributed to the development of image and video processing and compression at AT&T Bell Labs (Murray Hill), and multi-dimensional data processing and visualization at Schlumberger. Later in my career, I directed the research and development of image/video processing, compression, computer vision, machine learning, autonomous systems and robotics technologies and I collaborated on projects in these areas with various industries, including but not limited to Intel, NTT, Motorola, Freescale, NXP, General Dynamics, and NASA. More recently, I took on the role

of Chief Technical Advisor/CTO at AIAEC, LLC, supervising work and product development in the field of AI and machine learning.

13. At ASU, I helped in establishing two graduate programs, the Computer Engineering Program and the Robotics and Autonomous Systems (RAS) Program. I also developed and taught courses and supervised both undergraduate and graduate-level projects related to autonomous systems and robotics, mapping and navigation, sensing, perception, machine learning, signal processing, embedded systems, and associated computer-implemented control and processing. I served as ADAS lead advisor as part of the DoE/GM-sponsored Advanced Vehicular Technologies (AVTC) ECOCAR (EcoCAR3) Mobility Challenge in collaboration with various industry partners. I established and led an industry-academia-government collaborative initiative on automated mobility together with Intel, ADOT, DPS and GPEC as founding partners, which culminated in the establishment of the Governor's Institute on Automated Mobility at the state level.

14. The developed computer vision and machine learning systems for automated defect detection, 3D characterization, gender/age prediction, and autonomous vehicles were adopted at Intel. The developed image-based non-wet solder joints detection system was granted a Divisional Recognition Award by Intel. More details can be found in A.F. Said, B.L. Bennett, L.J. Karam, and J.S. Pettinato, "Robust Automatic Void Detection in Solder Balls," *IEEE International Conference*

on *Acoustics, Speech, and Signal Processing (ICASSP)*, pp. 1650-53, March 2010; A.F. Said, B.L. Bennett, F. Toth, L.J. Karam, and J.S. Pettinato, “Non-Wet Solder Joint detection in Processor Sockets and BGA Assemblies,” *Electronic Components and Technology Conference (ECTC)*, pp. 1147-53, May 2010; and in A.F. Said, B.L. Bennett, L.J. Karam, and J.S. Pettinato, “Automated Detection and Classification of Non-Wet Solder Joints,” *IEEE Transactions on Automation Science and Engineering*, vol. 8, no. 1, pp. 67-80, Jan. 2011. The developed image-based automated void detection system helped in enabling two industry standards, JEDEC JC 14-1 void guideline and IPC-7095C. More details can be found in A.F. Said, B.L. Bennett, L.J. Karam, A. Siah, K. Goodman, and J.S. Pettinato, “Automated Void Detection in Solder Balls in the Presence of Vias and Other Artifacts,” *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 2, no. 11, pp. 1890-901, Nov. 2012. More details about the developed 3D characterization system, including image-based solder ball height and warpage measurements, can be found in J. Li, B.L. Bennett, L.J. Karam, and J.S. Pettinato, “Stereo Vision Based Automated Solder Ball Height and Substrate Coplanarity Inspection,” *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 2, pp. 757-71, Apr. 2016; and in L. Karam and J. Li, “Stereo Vision Measurement System and Method,” U.S. Patent No. 9,704,232 B2, issued July 11, 2017. Details about machine-learning-based computer vision for defect detection

can be found in B.M. Haddad, S. Yang, L.J. Karam, J. Ye, N.S. Patel, and M.W. Braun, “Multi-Feature, Sparse-Based Approach for Defects Detection and Classification in Semiconductor Units,” *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 1, pp. 145-59, Jan. 2018; and in B.M. Haddad, S.F. Dodge, Yang, L.J. Karam, Ye, N.S. Patel, and M.W. Braun, “Locally Adaptive Statistical Background Modeling with Deep Learning-Based False Positive Rejection for Defect Detection in Semiconductor Units,” *IEEE Transactions on Semiconductor Manufacturing*, vol. 33, no. 3, pp. 357-72, Aug. 2020.

15. The developed 3D imaging and computer vision systems for autonomous vehicles include Advanced Driver Assist Systems (ADAS) technologies. The developed real-time forward collision warning system prototype was demonstrated by our Intel industry collaborators at the 2015 Consumer Electronics Show (CES) in Las Vegas. More details can be found in C.D. Prakash, J. Li, F. Akhbari, and L.J. Karam, “Sparse Depth Calculation Using Real-Time Key-Point Detection and Structure from Motion for Advanced Driver Assist Systems,” in G. Bebis et al. (eds.), *Advances in Visual Computing*, ISVC 2014, Lecture Notes in Computer Science, pp. 740-751, Dec. 2014; and in C.D. Prakash, F. Akhbari, and L.J. Karam, “Robust Obstacle Detection for Advanced Driver Assistance Systems Using Distortions of Inverse Perspective Mapping of a Monocular Camera,” *Robotics and Autonomous Systems*, vol. 114, pp. 172-86, Apr. 2019.

16. In addition, I directed the development of automated biomedical image processing and imaging technologies. The developed automated biomedical image processing technologies enabled high-throughput cancer diagnostics and drug discovery and were licensed for cancer research at different industries and institutions, including the Translational Genomics Institute (TGEN) and the New York School of Medicine. More details can be found in L.J. Karam and A. Said, “Automatic Cell Migration and Proliferation Analysis,” U.S. Patent No. 9,082,164 B2, issued July 14, 2015; A.F. Said, L.J. Karam, and S.R. Gehler, “Use of Muscale CMA_{cfz} Automated Image Analysis Software to Accurately Quantitate Cell Migration,” *16th Annual Society for Biomolecular Sciences Conference (SBS)*, Apr. 2010; A. Said and L.J. Karam, “Cell Migration Analysis using a Statistical Level-Set Segmentation on a Wavelet-Based Structure Tensor Feature Space,” *7th International Symposium on Signal Processing and Information Technology (ISSPIT)*, pp. 473-78, Dec. 2007; and in A. Said, L.J. Karam, M.E. Berens, Z. Lacroix, and R.A. Renaut, “Migration and Proliferation Analysis for Bladder Cancer Cells,” *IEEE International Symposium on Biomedical Imaging*, pp. 320-23, Apr. 2007.

17. The developed imaging technologies were adopted at medical institutions including the Barrow Neurological Institute (BNI). More details can be found in B. Kanberoglu, J.P. Debbins, and L.J. Karam, “Accurate Brain Tumor

Biopsy Using 3D ^1H -MRS Neuronavigation,” *18th Annual ISMRM meeting*, April 2010; B. Kanberoglu, L.J. Karam, J.P. Debbins, “Context-Based GRAPPA Reconstruction using a Small Kernel,” *18th Annual ISMRM meeting*, April 2010; B. Kanberoglu, T. Trouard, L. Karam, and J.P. Debbins, “Scanner Calibration For Multisite Geometric Accuracy: How To Do It,” *17th Annual ISMRM meeting*, April 2009; B. Kanberoglu, N. Zobenica, R. Ryan, M. C. Preul, L.J. Karam, and J.P. Debbins, “Accurate Brain Tumor Biopsy Using 3D ^1H -MRS Neuronavigation,” *17th Annual ISMRM meeting*, April 2009; C-Y Lee, L.J. Karam, and J.P. Debbins, “High-Order Diffusion Imaging Used to Differentiate Cytotoxic and Vasogenic Edema in Humans,” *17th Annual ISMRM meeting*, April 2009; B. Lenoski, L.C. Baxter, L.J. Karam, J. Maisog, and J.P. Debbins, “On the Performance of Autocorrelation Estimation Algorithms for fMRI Analysis,” *IEEE Journal on Special Topics in Signal Processing, Special Issue on Functional Magnetic Resonance Imaging*, vol. 2, no. 6, pp. 828-38, Dec. 2008; B. Lenoski, L. Karam, J. Debbins, and L. Baxter, “Autocorrelation Correction Methods in Clinical fMRI: Fixed Versus Variable P-Value Thresholding of 3T fMRI Datasets,” *13th Annual Meeting Human Brain Mapping*, Jun. 2007; and in B. Lenoski, L. Karam, L. Baxter, and J. Debbins, “Clinical Significance of Global versus Local fMRI Autocorrelation Estimation,” *Joint Annual Meeting ISMRM-ESMRMB*, Berlin, Germany, May 2007.

18. Furthermore, I directed the development of scalable visual compression technologies. The developed codecs were commercialized by General Dynamics. More details can be found in W.-J. Chien, N.G. Sadaka, G.P. Abousleman, and L.J. Karam, "Region-of-Interest-Based Ultra-Low-Bit-Rate Video Coding," SPIE Symposium on Defense & Security, Mar. 2008. I directed the development of perceptual-based visual compression methods and algorithms. The work on JPEG2000 Encoding with Perceptual Distortion Control enabled the integration of adaptive perceptual-based visual processing and compression in the JPEG 2000 image coding standard and demonstrated improved performance in terms of visual quality and compression while maintaining full compatibility with the JPEG 2000 standard.

19. My work has been published numerous times in prestigious journals, including *IEEE Transactions on Signal Processing*, *IEEE Transactions on Image Processing*, *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, *IEEE Transactions on Broadcasting, Robotics and Autonomous Systems*, and *IEEE/CVF Computer Vision and Pattern Recognition (CVPR) Conference*. Some selected publications include L.J. Karam, "Two-Dimensional FIR Filter Design by Transformation," *IEEE Transactions on Signal Processing*, vol. 47, pp. 1474-1478, May 1999; Y.M.Y. Hassan, L.J. Karam, "Morphological Reversible Contour Representation," *IEEE Transactions on Pattern Analysis and Machine*

Intelligence, vol. 22, no. 3, pp. 227-240, Mar. 2000; Y.M.Y. Hassan, L.J. Karam, "Morphological Text Extraction from Images," IEEE Transactions on Image Processing, vol. 9, no. 11, pp. 1978-83, Nov. 2000; I. Höntsch, L.J. Karam, "Adaptive Image Coding with Perceptual Distortion Control," IEEE Transactions on Image Processing, vol. 11, no. 3, pp. 213-222, March 2002; R. Ferzli, L.J. Karam, "A No-Reference Objective Image Sharpness Metric Based on the Notion of Just Noticeable Blur (JNB)," IEEE Transactions on Image Processing, vol. 18, no. 4, pp. 717-28, Apr. 2009; S. Varadarajan, L.J. Karam, D. Florencio, "Background Recovery from Video Sequences using Motion Parameters," IEEE International Conference on Speech, and Signal Processing (ICASSP), pp. 989-992, Apr. 2009; L.J. Karam, I. AlKamal, A. Gatherer, G. Frantz, D. Anderson, B. Evans, "Trends in Multi-Core DSP Platforms," IEEE Signal Processing Magazine, Special Issue on Signal Processing on Platforms with Multiple Cores, pp. 38-49, Nov. 2009; S. Varadarajan, L.J. Karam, D. Florencio, "Background Subtraction using Spatio-Temporal Continuities," European Workshop on Visual Information Processing (EUVIP), pp. 144-148, July 2010; A.F. Said, B.L. Bennett, L.J. Karam, and J.S. Pettinato, "Automated Detection and Classification of Non-Wet Solder Joints," IEEE Transactions on Automation Science and Engineering, vol. 8, no. 1, pp. 67-80, Jan. 2011; S. Chikkerur, V. Sundaram, M. Reisslein, and L.J. Karam, "Objective Video Quality Assessment Methods: A Classification, Review, and Performance

Comparison,” IEEE Transactions on Broadcasting, vol. 57, no. 2, pp. 165-182, June 2011; L.J. Karam, N.G. Sadaka, R. Ferzli, Z.A. Ivanovski, “An Efficient Selective Perceptual-Based Super-Resolution Estimator,” IEEE Transactions on Image Processing, vol. 20, no. 12, pp. 3470-82, Dec. 2011; J. Li, L.J. Karam, “Depth Estimation from Multi-View Images,” International Conference on Emerging Signal Processing Applications (ESPA), pp. 151-154, Jan, 2012; S.F. Dodge, L.J. Karam, "Attentive Gesture Recognition," IEEE International Conference on Image Processing (ICIP), pp. 177-180, Sep. 2012; B. Kanberoglu, N.Z. Moore, D. Frakes, L.J. Karam, J.P. Debbins, M.C. Preul, “Integration of 3D ¹H-magnetic resonance spectroscopy data into neuronavigation systems for tumor biopsies,” Proceedings of SPIE, Medical Imaging, Image-Guided Procedures, Robotic Interventions, and Modeling, vol. 8671, id. 86711B, 7 pages, March 2013; S.F. Dodge, L.J. Karam, “Is Bottom-Up Attention Useful for Scene Recognition?,” 6th International Symposium on Attention in Cognitive Systems (ISACS), held in conjunction with the International Joint Conference on Artificial Intelligence (IJCAI), 10 pages, Aug. 2013; A. Shroter, L.J. Karam, “Background recovery from multiple images,” IEEE Digital Signal Processing Workshop, pp. 135-140, Aug. 2013; L.J. Karam, W.B. Kleijn, K. MacLean, “Perception-based Media Processing,” Proceedings of the IEEE, vol. 101, no. 9, pp. 1900-1904, Sep. 2013; S. Dodge, L. Karam, “An Evaluation of Attention Models for Use in SLAM,” Proc. SPIE 9025, Intelligent

Robots and Computer Vision XXXI: Algorithms and Techniques, 90250M, Feb. 2014; B. Kanberoglu, N.Z. Moore, D. Frakes, L.J. Karam, J.P. Debbins, M.C. Preul, "Neuronavigation using Three-Dimensional Proton Magnetic Resonance Spectroscopy Data," *Stereotactic and Functional Neurosurgery*, pp. 306-314, vol. 92, no. 5, Sep. 2014; Q. Xu, S. Varadarajan, C. Chakrabarti, and L.J. Karam, "A Distributed Canny Edge Detector: Algorithm and FPGA Implementation," *IEEE Transactions on Image Processing*, vol. 23, no. 7, pp. 2944-2960, July 2014; C. Prakash, J. Li, F. Akhbari, L. Karam, "Sparse Depth Calculation using Real-time Key-point Detection and Structure from Motion for Advanced Driver Assist Systems," *Springer Lecture Notes, ISVC*, pp. 740-751, Dec. 2014; J. Andrade, C. Prakash, F. Akhbari, L.J. Karam, "Low-Complexity and Low-Delay Structure from Motion Approach for Advanced Driver Assist Systems," *International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV)*, pp. 191-197, 2015; Varadarajan, L.J. Karam, "A No-Reference Texture Regularity Metric Based On Visual Saliency," *IEEE Transactions on Image Processing*, vol. 24, no. 9, pp. 2784-2796, Sep. 2015; J. Li, B.L. Bennett, L.J. Karam, J.S. Pettinato, "Stereo Vision Based Automated Solder Ball Height and Substrate Coplanarity Inspection," *IEEE Transactions Automation Science and Engineering*, vol. 13, no. 2, pp. 757-771, April 2016; M.M. Subedar and L.J. Karam, "3D Blur Discrimination," *ACM Transactions on Applied Perception*, vol. 13, no. 3, pp. 1-13, May 2016; S.F. Dodge,

L.J. Karam, “Understanding How Image Quality Affects Deep Neural Networks,” International Conference on the Quality of Multimedia Experience (QoMEX), 6 pages, June 2016; S.A. Golestaneh and L.J. Karam, “Spatially-Varying Blur Detection Based on Multiscale Fused and Sorted Transform Coefficients of Gradient Magnitudes,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 596-605, July 2017; S. Dodge, J. Mounsef, and L. Karam, “Unconstrained Ear Recognition Using Deep Neural Networks,” IET Biometrics, vol. 7, no. 3, pp. 207-214, Jan. 2018; L.J. Karam, T. Borkar, J. Chae, Y. Cao, “Generative Sensing: Transforming Unreliable Data for Reliable Recognition,” IEEE Multimedia Information Processing and Retrieval (IEEE MIPR), Apr. 2018; S.F. Dodge and L.J. Karam, “Visual Saliency Prediction Using a Mixture of Deep Neural Networks,” IEEE Transactions on Image Processing, vol. 27, no. 8, pp. 4080-90, Aug. 2018; S.F. Dodge and L.J. Karam, “Quality Robust Mixtures of Deep Neural Networks,” IEEE Transactions on Image Processing, vol. 27, no. 11, pp. 5553-62, Nov. 2018; J. Mounsef and L. Karam, “Augmented Sparse Representation Classifier (ASRC) for Face Recognition Under Quality Distortions,” IET Biometrics, vol. 8, no. 6, pp. 431-442, Oct. 2019; T.S. Borkar and L.J. Karam, “DeepCorrect: Correcting DNN Models Against Image Distortions,” IEEE Transactions on Image Processing, vol. 28, no. 12, pp. 6022-34, Dec. 2019; and in C.D. Prakash and L.J. Karam, “It GAN Do Better: GAN-based Detection of Objects

on Images with Varying Quality,” IEEE Transactions on Image Processing, vol. 30, pp. 9220-30, Nov. 2021.

20. I am an inventor, and I have been awarded eight patents in the fields of image and video processing, compression, transmission, computer vision, and machine learning: U.S. Patent Nos. 6,154,493 (“The Compression of Color Images Based on a 2-Dimensional Discrete Wavelet Transform Yielding a Perceptually Lossless Image”), 6,124,811 (“Real-time Algorithms and Architectures for Coding Images Compressed by DWT-Based Techniques”), 6,717,990 (“Communication System and Method for Multi-Rate, Channel-Optimized Trellis-Coded Quantization”), 7,551,671 (“System and Method for Transmission of Video Signals Using Multiple Channels”), 9,082,164 (“Automatic Cell Migration and Proliferation Analysis”), 9,501,710 (“Systems, Methods, and Media for Identifying Object Characteristics Based on Fixation Points”), and 9,704,232 (“Stereo Vision Measurement System and Method”), and 11,0304,85 (“Systems and Methods for Feature Corrections and Regeneration for Robust Sensing, Computer Vision, and Classification”). I am also a named inventor on two additional patent applications, published as U.S. 2008/0259796 (“Method and Apparatus for Network-Adaptive Video Coding”) and as WO PCT Application PCT/US24/56544 (WO 2025/097186) (“Systems, Methods, and Media for Generating Documents Using Machine Learning”).

21. Based on my background, experience, education, and professional activities, I consider myself an expert in the fields of signal processing, image and video processing, computer vision (2D and 3D), machine learning, sensing, robotics, and associated computer-implemented control and processing. I am not an attorney and offer no legal opinions, but, in my work, I have had experience studying and analyzing patents and patent claims from the perspective of a person skilled in the art. I believe that I am qualified to opine as to the knowledge and level of skill of a POSITA at the time of the '325 patent (which I further describe below), in addition to the general state of the art during that time.

III. Legal Understandings

22. In this section, I describe my understanding of certain legal standards that I may have relied upon in forming my opinions set forth in this declaration. I have been informed of these legal standards by Petitioners' attorneys. Although I am not an attorney and have not researched the law on patent invalidity, I have formed the following understanding about the legal standards through Petitioners' attorneys.

A. A Person of Ordinary Skill in the Art

23. I understand there are multiple factors relevant to determining the level or ordinary skill in the pertinent art, including (1) the levels of education and experience of persons working in the field at the time of the invention; (2) the

sophistication of the technology; (3) the types of problems encountered in the field; and (4) the prior art solutions to those problems.

24. I further understand that the hypothetical POSITA is presumed to have knowledge of all references that are sufficiently related to one another and to the pertinent art, and to have knowledge of all arts reasonably pertinent to the particular problem that the claimed invention purports to address.

25. In my opinion, as it relates to the '325 patent, a person of ordinary skill in the art around November of 2016 would have had a Bachelor's degree or higher in electrical, computer, or mechanical engineering or computer science (or equivalent discipline) and at least two years of experience in research, design and/or development or autonomous robotics and/or robotic mapping/navigation and/or a related field. This experience might have included, for example, sensing, perception, signal processing, computer vision, and/or associated computer-implemented control and processing. Additional education might substitute for less work experience, or vice versa.

26. I meet the criteria described above and believe myself to be a person with at least ordinary skill in the art pertaining to the '325 patent. I would have qualified as such a person by at least November 1, 2016, which I understand is the earliest priority date of the '325 patent.

27. For the purposes of this Declaration, in general, and unless otherwise noted, my statements and opinions, such as those regarding my own experience and what a POSITA would have understood or known generally (and specifically related to the references I consulted herein), reflect the knowledge that existed in the relevant field as of the priority date of the '325 patent.

B. Legal Standard for Prior Art, Anticipation, and Obviousness

28. I understand that prior art to the '325 patent includes patents and printed publications in the relevant art that predate the priority date of the '325 patent. For the purposes of this Declaration, I am applying November 1, 2016, as the priority date of the '325 patent.

29. I have been informed by counsel that a claimed invention is unpatentable under the AIA 35 U.S.C. § 102 if a single prior-art reference discloses to a POSITA each limitation of the invention, and that such disclosure may be explicit or inherent. I have also been informed by counsel that whether a reference discloses each limitation is a question of fact.

30. I have been informed by counsel that a claimed invention is unpatentable under the AIA 35 U.S.C. § 103 if the differences between the claimed invention and the prior art are such that the subject matter as a whole would have been obvious to a POSITA at the time of filing. I have also been informed by counsel that the obviousness analysis considers factual inquiries, including the level of

ordinary skill in the art, the scope and content of the prior art, and the differences between the prior art and the claimed subject matter.

31. I have been further informed by counsel that there are several recognized rationales for combining references or modifying a reference to show obviousness. These rationales include: (a) combining prior art elements according to known methods to yield predictable results; (b) simple substitution of one known element for another to obtain predictable results; (c) use of a known technique to improve a similar device (method, or product) in the same way; (d) applying a known technique to a known device (method, or product) ready for improvement to yield predictable results; (e) choosing from a finite number of identified, predictable solutions, with a reasonable expectation of success; and (f) some teaching, suggestion, or motivation in the prior art that would have led a POSITA to modify the prior art or to combine prior art teachings to arrive at the claimed invention.

32. I understand that in evaluating whether patent claims are invalid as obvious, secondary considerations of non-obviousness are considered, including considerations such as commercial success, long-felt but unsolved needs, copying, praise, teaching away from the claimed invention by the prior art, unexpected results, industry acceptance, failure of others, and skepticism by experts. I understand that the secondary considerations are considered with the balance of obviousness evidence in the record to act as a check against impermissible hindsight bias. I

further understand that there must be a nexus between the merits of the claimed invention and the evidence of secondary considerations in order to give such considerations substantial weight in the determination of obviousness.

33. I understand that the burden of presenting evidence of secondary considerations is on the Patent Owner. I also understand that the proponent of the evidence of secondary considerations bears the burden of showing that a nexus exists between the claimed features of the invention and the evidence offered to show nonobviousness.

C. General Claim Construction Principles

34. I understand that there are two types of claims: independent claims and dependent claims. I understand that an independent claim stands alone and includes only the limitations it recites. I understand that a dependent claim is a claim that depends on another claim. I understand that a dependent claim includes all of the limitations recited in the dependent claim as well as any limitations included in the corresponding independent claim.

35. I understand that before determining whether the Challenged Claims are invalid, the claims must be construed on a limitation-by-limitation basis. I understand that claim terms are to be afforded their plain and ordinary meaning as used in the claims and as would be understood by a POSITA at the time of the filing. I understand that this person skilled in the art at the time of the invention is assumed

to have read the claim terms in light of the entire patent record, including the other claims, the patent specification, and the patent prosecution history. I have interpreted the claim terms in the '325 patent in light of this understanding.

36. I understand that to properly understand the meaning of claim terms, one should first consider the intrinsic evidence, which includes the claim language itself, the patent specification, and the patent's prosecution, as well as any post-issuance history before the Patent Office. For example, the patent specification may show that the inventor used words or terms in a manner inconsistent with their plain and ordinary meaning. Specifically, I understand that where the specification reveals a special definition given to a claim term by the inventor that differs from the meaning it would otherwise possess, the inventor's lexicography governs. I understand that the prosecution history of the patent may also provide guidance in construing a claim term. For example, the prosecution history may show that the patent applicant might have limited the scope of some or all of the claims during prosecution, either affirmatively or by implication.

37. I understand that if the intrinsic evidence is not conclusive regarding the meaning of a particular claim term, extrinsic evidence may also be used to determine its meaning. I understand that extrinsic evidence may be used, for example, to help determine what a person skilled in the art at the time of the

invention would have understood the claim term to mean. Extrinsic evidence may include dictionaries, technical treatises and books, articles, or expert testimony.

IV. BACKGROUND TECHNOLOGY

38. To put in context my opinions on the validity of the claims of the '325 patent, in this section I provide a brief discussion of the relevant technological background, which relates to robotic mapping.

39. Researchers have investigated sensor-enabled autonomous robotic navigation and mapping since at least the 1980s. For example, Smith and Cheesman published “On the Representation and Estimation of Spatial Uncertainty” in 1986, which “describes a general method for estimating the nominal relationship and expected error (covariance) between coordinate frames representing the relative locations of objects” using sensor measurements of the environment, and explains that the method can be used for reducing uncertainty in robotic mapping and navigation. Ex1009, 56, 63. Chatila and Laumond published “Position Referencing and Consistent World Modeling for Mobile Robots” in 1985, discussing a robot that uses multiple sensors to identify landmarks and map its environment. Ex1010.

40. In the 1990s, researchers began to use the term Simultaneous Localization and Mapping (SLAM) to describe robotic mapping. Ex1011, 100. As Stachniss and colleagues explain, SLAM may be understood as the definition of a problem (e.g., “[t]he SLAM problem” (Ex1005, 1153)), or it may be understood as

a collection of techniques for solving that problem (Ex1005, 1156–66). Stachniss provides a taxonomy classifying those techniques, (e.g., “Volumetric Versus Feature-Based” and “Active Versus Passive” (Ex1005, 1156–57)), and further divides SLAM approaches into three paradigms (Extended Kalman Filters, Particle Methods, and Graph-Based Optimization Techniques (Ex1005, 1157–66)). Stachniss also explains that various researchers have combined techniques from these paradigms into hybrid approaches. Ex1005, 1164–65.

41. Certain SLAM algorithms rely on visual sensor data, like cameras, RGD-D sensors, and the like. As with other SLAM techniques, these algorithms likewise have a long pedigree. For example, Davidson and Murray published “Mobile Robot Localisation Using Active Vision” in 1998, describing an automated feature-tracking and mapping robot. Ex1012. Stachniss lists more than a dozen Visual SLAM implementations, published from 1980 through 2013. Ex1005, 1166–69.

42. SLAM algorithms have also used loop closures to improve the precision of their maps, including based on information from visual sensors, before the priority date of the challenged patent. Lu and Milos published their seminal paper on loop closure in 1999, wherein they disclosed an algorithm to implement loop closure with range scans and the maps which the algorithm generated. Ex1013. Later that same year, Gutman and Konolige published “Incremental mapping of

large cyclic environments,” which cited Lu and Milos and disclosed a robot that mapped space in real-time with a graph-SLAM method implementing loop closure. Ex1023. In 2011, Grisetti and colleagues published a tutorial on SLAM which implements loop closure using 2-D and 3-D laser scanners. Ex1014. In 2012, Henry and colleagues published a paper implementing loop closure based on an RGB-D camera, and explained that “[c]olor cameras . . . capture rich visual information and are becoming more and more the sensor of choice for loop closure detection.” Ex1015, at 1.

43. Practitioners have integrated these concepts into practical applications for many years. The Second Edition of the Handbook of Robotics, which includes two references used in the grounds of the petition (Stachniss (Ex1005) and Prassler (Ex1007)), dedicates a section to practical robotics. Ex1016, 1381–1784.

44. Additionally, practitioners published open-source software packages to enable autonomous robotic mapping using SLAM before the priority date of the challenged patent. For example, Grisetti, Stachniss, and Burgard developed a software package that uses laser-scan data to build maps, “gmapping,” and released that package in the open-source Robot Operating System (ROS) in 2007. Ex1017, 2. The documentation explains that the package is built using insights from the papers published by Grisetti and colleagues in 2005 and 2007. Ex1018; Ex1019; Ex1020. A POSITA would have viewed these ROS open-source packages as an

important and available tool to enable practical robots, including to perform robotic mapping. Indeed, in July of 2015, ROS binaries had been downloaded from nearly fifty thousand different IP addresses. Ex1021.

45. In sum, a POSITA interested in robotic mapping would have understood that a range of prior art techniques existed, including techniques that used pose-graphs and loop closures. The POSITA would have further understood that these techniques had already been implemented in a range of practical devices. And the POSITA would have known that there were open-source tools available to them to implement their own robotic mapping solutions.

V. The '325 patent

A. Summary of the '325 patent

46. The '325 patent “relates generally to robotics, and more specifically to systems and methods for robotic mapping.” Ex1001, 1:25–27. It discloses systems and methods for robotic mapping, wherein a map of an environment is generated concurrently with traveling through the environment. Ex1001, Abstract, 1:65–2:12. The map is generated from “a graph comprising a plurality of nodes, wherein each node corresponds to a scan taken by a sensor of the robot at a location in the environment,” representing the path the robot traveled as it mapped the environment, and a representation of the environment as captured through sensors mounted on the robot. Ex1001, Abstract, 1:65–2:12. Sensor scans are associated with nodes, and

are matched together to make up the environment. Ex1001, Abstract, 1:65–2:12, 15:1–14, 18:4–12.

B. Summary of the Prosecution History of the '325 Patent

47. The '325 Patent's application, U.S. Patent Application No. 15/340,807 ('807 Application), was filed on November 1, 2016, and the '325 Patent issued on April 30, 2019. Ex1001, 1. 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, 70.

48. The Applicant amended the claims once during prosecution and prior to allowance in response to a Non-Final Rejection. Ex1002, 268–76. The Examiner issued a Non-Final Rejection on May 31, 2018, in which 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 the remaining claims as being dependent upon rejected independent claims 8 and 16. Ex1002, 212–16.

49. After an Examiner Interview on August 21, 2018 (Ex1002, 275), the Applicant responded to the Non-Final Rejection by amending the claims on August 28, 2018 (Ex1002, 269–74). The Applicant removed certain limitations from claim 1 and added substantially similar limitations to dependent claim 2, and revised other limitations of claim 1. Ex1002, 269–70. The changes for claim 1 are depicted in an excerpt from the prosecution history, reproduced below.

1. (Currently Amended) A method of generating a map by a robot, comprising:

- traveling, by the robot, in an environment;
- ~~creating~~ generating a graph comprising a plurality of nodes, ~~wherein each a respective~~ node of the plurality of nodes corresponds to a scan ~~taken~~ generated by a sensor of the robot at a location in the environment;
- ~~constraining the graph to start and end at a substantially similar location;~~
- performing scan matching on extended scan groups, the extended scan groups being determined at least in part from groups in-part on at least two or more nodes of the plurality of nodes; and
- 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
- ~~associating a range of possible locations with each of the plurality of nodes based at least in part on the scan matching;~~
- ~~determining confidences associated with each range of possible locations;~~
- ~~optimizing the graph to find a likely location of the plurality of nodes based at least in part on the associated confidences; and~~
- ~~generating the map from the optimized graph.~~

Ex1002, 269.

50. The Applicant further added one limitation from claim 1, “constraining the graph . . .,” to each of the independent claims (issued claims 8 and 15). Ex1002, 271–74. The changes for claim 8 are depicted in an excerpt from the prosecution history, reproduced below.

8. (Currently Amended) A robot, comprising:

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

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

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

determine extended scan groups ~~based at least in part on groups in-part on at least~~
two or more nodes of the plurality of nodes; [[and]]

perform scan matching on the extended scan groups; and

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.

Ex1002, 271–72.

51. Accordingly, the Examiner found that the inclusion of the limitation, “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,” rendered each independent claim of the ’325 Patent patentably distinguishable from Eade. However, as discussed more fully below (*see infra* §§ VII.A.1.e, VII.B.1.e), such constraints were well-known in the robotic mapping art as “loop closure,” or “loop closing” as were each of the other limitations claimed in the ’325 Patent.

C. Overview of the Challenged Claims

52. There are three independent claims in the '325 patent: claims 1, 8, and 15. Claim 1 is a method claim, and claims 8 and 15 are apparatus claims.

53. I understand that Petitioners are challenging all of the claims in the '325 patent (the "Challenged Claims"). I have analyzed each of these claims.

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

No.	Limitation
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.
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 [sic] 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.

54. For the reasons I detail below, it is my opinion that each of these claims is unpatentable over the prior art discussed below.

VI. Prior Art Considered

55. In this declaration, I provide four prior art references (among others) with exemplary citations identifying the relevant features related to the claim language of the Challenged Claims. I have also described combinations of these prior art references that, when combined, render the Challenged Claims obvious. It is my opinion that the Challenged Claims are anticipated and/or rendered obvious in light of the prior art specifically discussed in this declaration.

56. The citations presented in the body of this declaration correspond to the teachings disclosed in exemplary items of prior art that identify: (1) the problem(s)

confronted by one of ordinary skill in the art; (2) an express suggestion to make one or more of the combinations; (3) an implicit suggestion to make one or more of the combinations; or (4) the knowledge of those skilled in the art as to the applicable field of technology.

A. Identification of the Primary Prior Art References

57. It is my opinion that a person of ordinary skill would consider at least the prior art references below:

Prior Art Reference	Qualifying Date	Exhibit No.
Edwin B. Olson, <i>Robust and Efficient Robotic Mapping</i> , Massachusetts Institute of Technology, June 2008 (“Olson”)	July 1, 2008	1004
Stachniss et al., <i>Springer Handbook of Robotics, Chapter 46: Simultaneous Localization and Mapping</i> , Springer (2 nd ed.) (“Stachniss”)	January 31, 2016	1005
U.S. Patent No. 9,538,892 (“Fong”)	October 5, 2012	1006
U.S. Patent No. 9,020,637 (“Schnittman”)	March 8, 2013	1007

58. A POSITA considering the problem of robotic mapping would search for printed publications that describe solutions to that problem. Such printed publications would include patents, journal articles, technical books and/or manuals, and other academic publications like doctoral theses. A POSITA would use search

terms that are readily apparent according to the nature of the problem, such as “robotic mapping,” “mobile robots,” “robotics,” “artificial intelligence,” or “automation.” It is my understanding that each of the references listed above would have been found using one or more of these search terms. Ex1008, ¶¶ 24, 30, 35.

59. Other references and knowledge described earlier in this declaration are relevant to show the state of the art – i.e., what a person of ordinary skill would have known when using the references identified above, or to use in combination with the references above to render the Challenged Claims invalid. The references include, but are not limited to:

- Smith, Randall C., and Peter Cheeseman. “On the representation and estimation of spatial uncertainty.” *The International Journal of Robotics Research* 5.4 (1986): 56-68 (Ex 1009).
- Chatila, Raja, and Jean-Paul Laumond. “Position referencing and consistent world modeling for mobile robots.” *Proceedings of the 1985 IEEE International Conference on Robotics and Automation*. (1985):138-145 (Ex1010).
- Durrant-Whyte, Hugh, and Tim Bailey. “Simultaneous localization and mapping: part I.” *IEEE Robotics & Automation magazine* 13.2 (2006): 99-110 (Ex1011).

- Davison, Andrew J., and David W. Murray. “Mobile robot localisation using active vision.” Proceedings of the 5th European Conference on Computer Vision. Springer Lecture Notes in Computer Science (LNCS), Vol. 1407, Volume II (1998):809-825 (Ex1012).
- Lu, Feng, and Evangelos Milios. “Globally consistent range scan alignment for environment mapping.” Autonomous Robots 4 (1997): 333-349 (Ex1013).
- Grisetti, Giorgio, et al. “A tutorial on graph-based SLAM.” IEEE Intelligent Transportation Systems Magazine 2.4 (2010): 31-43 (Ex1014).
- 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 (Ex1015).
- *Springer Handbook of Robotics*, Bruno Siciliano and Oussama Khatib eds., Springer 2nd ed., 2016 (Ex1016).
- Macenski, Steve, and Ivona Jambrecic. "SLAM Toolbox: SLAM for the dynamic world." Journal of Open Source Software 6.61 (2021): 2783. 7 pages (Ex1017).
- Giorgio Grisetti, Cyrill Stachniss, and Wolfram Burgard, *GMapping*, OpenSlam.org, <https://openslam-org.github.io/gmapping.html> (last visited Oct. 16, 2025) (Ex1018).

- Grisetti, Giorgio, et al. “Improving grid-based SLAM with Rao-Blackwellized particle filters by adaptive proposals and selective resampling.” Proceedings of 2005 the IEEE International Conference on Robotics and Automation (ICRA). (2005):2432-2437 (Ex1019).
- Grisetti, Giorgio, et al. “Improved techniques for grid mapping with Rao-Blackwellized particle filters.” IEEE Transactions on Robotics 23.1 (2007):34-46 (Ex1020).
- 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) (Ex1021).
- Gutmann, Jens-Steffen, 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 (Ex1023).

B. General Overview of the Primary Prior Art References

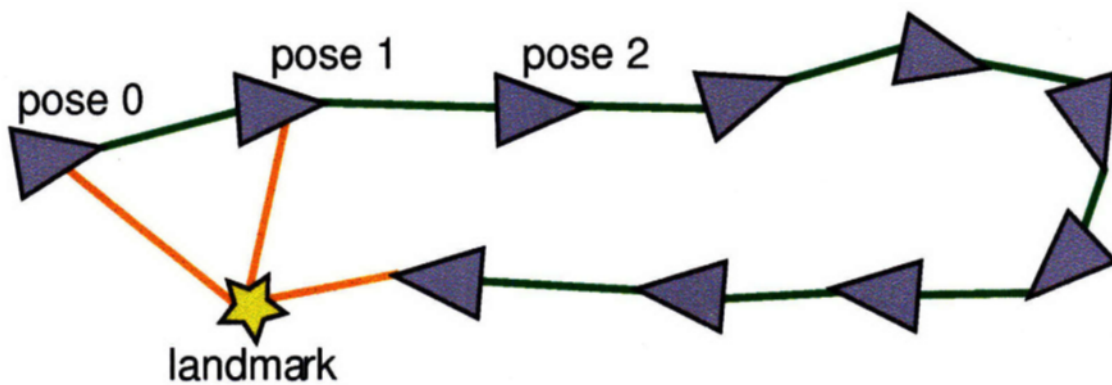
60. The following sections provide a brief description of the prior art systems and software that invalidate the '325 patent. This discussion is not meant to be exhaustive, and my full element-by-element analysis is provided in more detail below in the analysis section. I have personally reviewed the references cited in this declaration. It is my opinion that Olson and Stachniss each separately or in

combination with Fong or Schnittman disclose or suggest the features of the Challenged Claims.

**1. “Edwin B. Olson, *Robust and efficient mapping*,
Massachusetts Institute of Technology, June 2008”
 (“Olson”)**

61. “Robust and efficient robotic mapping,” by E. B. Olson, is a Ph.D thesis submitted to the Massachusetts Institute of Technology in 2008, and published later at least by 2009. Ex1008, ¶ 22.

62. Olson discloses a graph-based SLAM method capable of building a map of a large environment that is robust to noisy sensors. Ex1004, 3, 19–20, 34. Olson explains that his algorithm implements graphical SLAM, wherein a robot generates a map of an environment from a graph of nodes based on sensor data associated with each node. Ex1004, 19–20 (explaining the pose-graph concept), 32–54 (providing an overview of the loop closing method), 55–88 (describing batch-wise optimization of pose-graphs), 89–103 (describing incremental optimization of pose-graphs). Olson depicts a simplified graph in Figure 1-4 (reproduced below), which shows a robot that has navigated through several poses (*i.e.*, nodes), and has observed the same landmark from three of those positions. Ex1004, 15. As a result, each pose is relationally connected to the poses immediately prior and subsequent to it, as shown in the graph of Figure 1-4, and the nodes that observed the landmark are additionally connected to that landmark. Ex1004, 15, Figure 1-4.



Ex1004, Figure 1-4.

63. Olson further explains that the goal of graph-SLAM is to recover the most-likely position of each node, given all the data (e.g., from odometers and other sensors) available to the robot. Ex1004, 3, 12–16. This is accomplished through the “posterior probability distribution,” that is recovered using optimization procedures. Ex1004, 12–16. Olson provides a review of several SLAM optimization methods, including FastSLAM, (Ex1004, 12, 58), Gauss-Seidel, (Ex1004, 77–78), and Cholesky decomposition, (Ex1004, 74–76). Olson explains that it provides an algorithm to resolve a graph-SLAM optimization using a hybrid approach, including non-linear least-squares and stochastic gradient descent. Ex1004, 65–66. Olson explains that his algorithm may be performed in a batch mode based on all the data that has been collected so far, or in an incremental fashion as new data is collected allowing the “incorporat[ion] of new information without obliterating the results of previous iterations.” Ex1004, 89–90.

64. Olson implements its algorithm on datasets and shows the maps that result. For example, Figure 5-4 (reproduced below) shows resulting maps for the Intel Research Center dataset. Ex1004, 100-03, Figure 5-4.

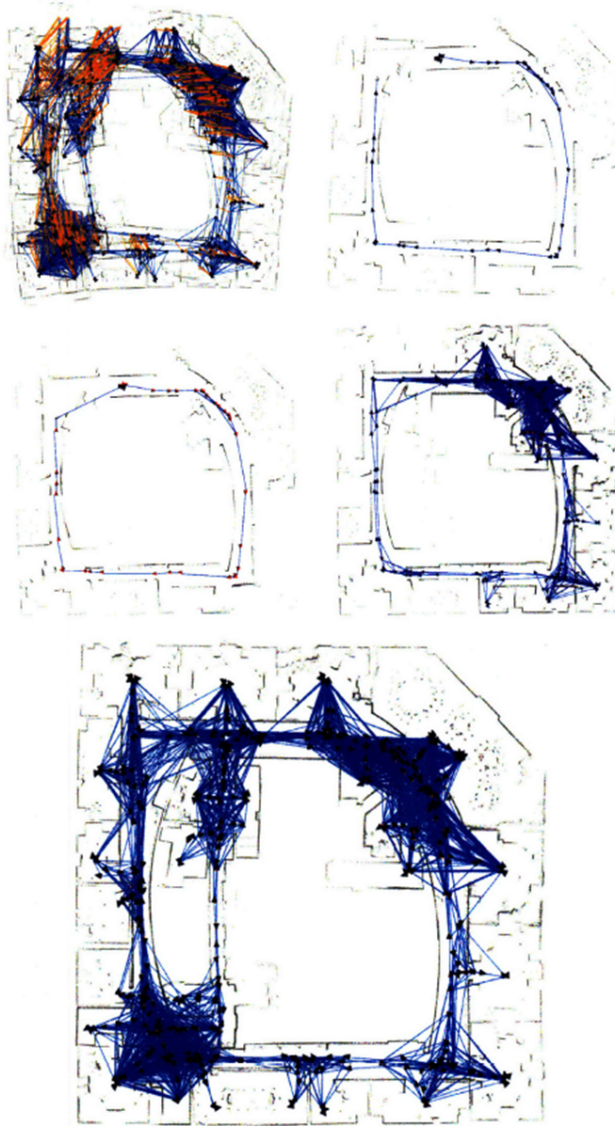


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

2. “Springer Handbook of Robotics (2nd ed.) Chapter 46: Simultaneous localization and mapping” (“Stachniss”)

65. “Springer Handbook of Robotics” second edition was publicly available by January 1, 2016. Ex1008, ¶ 28. The Springer Handbook of Robotics provided an overview on various aspects of robotics and sought to explain the foundational topics of robotics, and to highlight various designs and applications. It contained many chapters, written by over 200 experts in the field. Ex1016. Chapter 46 was written by Cyrill Stachniss, John J. Leonard and Sebastian Thrun, and is entitled “Simultaneous localization and mapping” (“Stachniss”). Ex1005, 1153. A POSITA would have known to look at The Springer Handbook of Robotics if the POSITA wanted to learn about certain aspects of robotics or wanted to implement different concepts into their design.

66. Stachniss specifically was written to give an overview of simultaneous localization and mapping (“SLAM”). Specifically: :

This chapter provides a comprehensive introduction in [*sic*] to the simultaneous localization and mapping problem, better known in its abbreviated form as SLAM. SLAM addresses the main perception problem of a robot navigating an unknown environment. While navigating the environment, the robot seeks to acquire a map thereof, and at the same time it wishes to localize itself using its map. The use of SLAM problems can be motivated in two different ways: one might be interested in detailed environment models, or one might seek to maintain an accurate sense of a mobile robot’s location. SLAM serves both of these purposes. We review the three major paradigms from which many published methods for SLAM are derived: (1) the extended Kalman filter (EKF); (2) particle filtering; and (3) graph optimization. We also review recent work in three-dimensional (3-D) SLAM using

visual and red green blue distance-sensors (RGB-D), and close with a discussion of open research problems in robotic mapping.

Ex1005, 1153.

67. Stachniss discloses various methods to solve the SLAM problem, including “Graph Based Optimization Techniques.” Ex1006, 1162–66. Specifically, Stachniss discusses the use of sensors, loop-closures and pictorial graphs to map unknown environments. Ex1007, 1166–69.

68. Stachniss discloses:

The SLAM problem is defined as follows: A mobile robot roams an unknown environment, starting at an initial location x_0 . Its motion is uncertain, making it gradually more difficult to determine its current pose in global coordinates. As it roams, the robot can sense its environment with a noisy sensor. The SLAM problem is a problem of building a map of the environment while simultaneously determining the robot’s position relative to this map given noisy data.

Ex1005, 1154.

69. As the robot moves, each node along the route is denoted by x_t , which represents the robot’s location at time t . Ex1005, 1154. The motion between locations x_{t-1} and x_t , provided by odometry data, is represented by u_t , and the sensor measurement at each location is represented by z_t . Ex1005, 1154. This is represented by Fig. 46.1 (reproduced below).

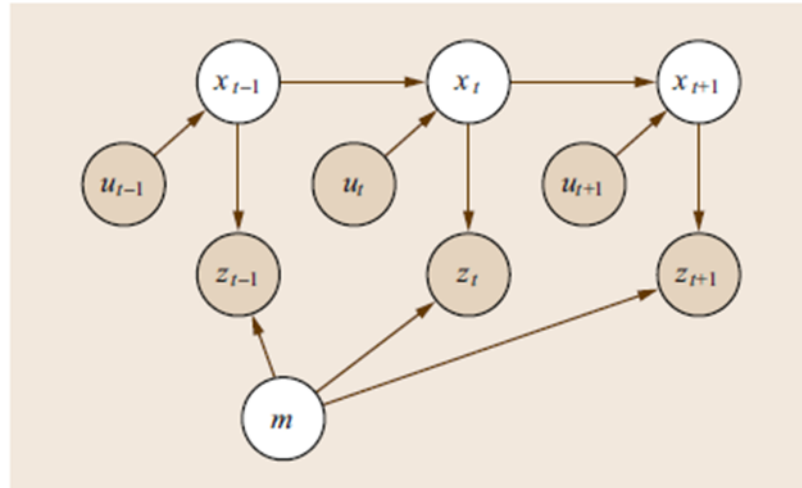


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

70. Stachniss explains that, in graph-based SLAM, “[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 . Further, edges exist between the nodes that correspond to location x_t and landmarks m_i , assuming that at time t the robot sensed landmark i .”

Ex1005, 1162. Fig. 46.7 (reproduced below) illustrates the construction of the graph in graph-based SLAM. Ex1005, 1163, Fig. 46.7a–c.

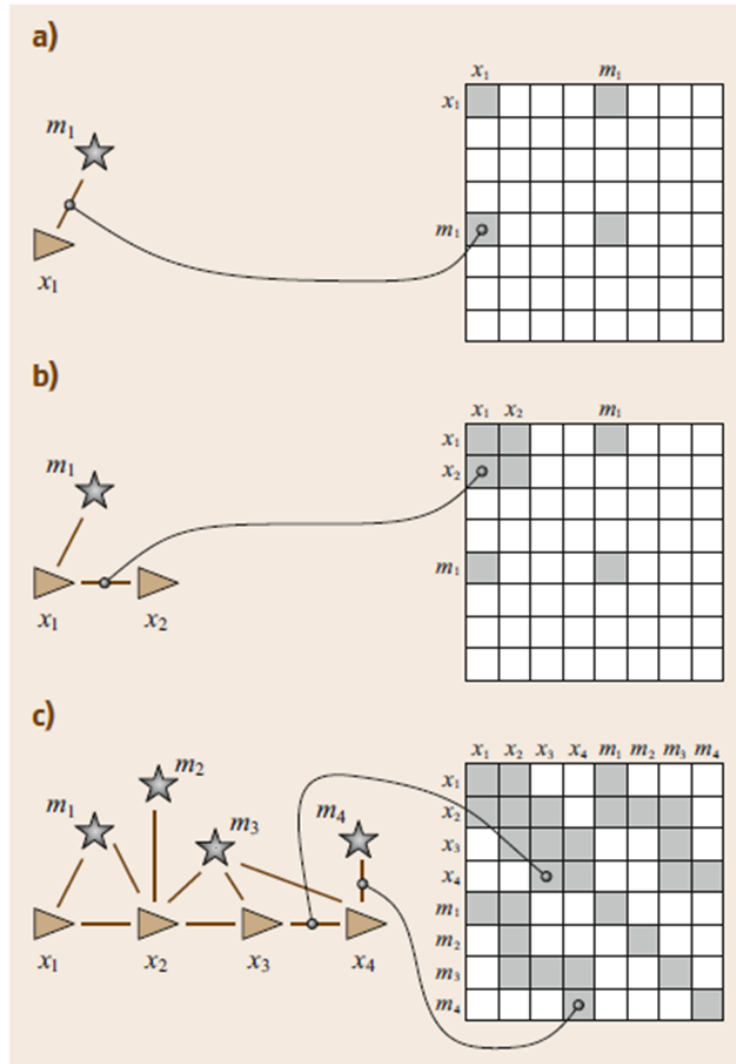
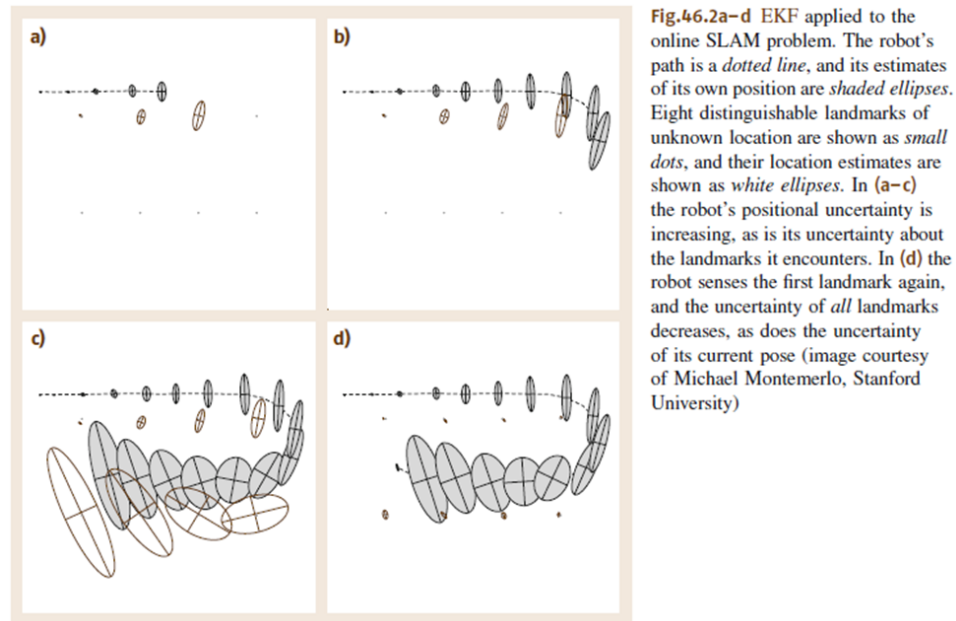


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation is landmark m_1 . (b) Robot motion from x_1 to x_2 . (c) Several steps later

Ex1005, Fig. 46.7a–c.

71. Stachniss also explains that each node (representing the robot's location at a time t , x_t) has a probability distribution providing the robot's location estimate and the uncertainty (or confidence measure) associated with the estimate. Ex1005, 1157–58. The more uncertain the exact location of the robot, the large the range of

uncertainty at a node, as depicted in Fig. 46.2 (reproduced below) by the size of the ellipses at each of the nodes along the robot's travel path. Ex1005, 1157–58.



Ex1005, Fig. 46.2a-d.

3. U.S. Patent No. 9,538,892 (“Fong”)

72. 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, published on April 10, 2014, and issued on January 10, 2017. It claims priority to US Provisional Application No. 61/710,422, filed on October 5, 2012. It was assigned to iRobot Corporation, and explains that it may be used with “any suitable robot,” including one “generally configured in the manner of or includ[ing] features from the Roomba™ floor cleaning robot.” Ex1006, 5:9–25. It describes a robot cleaning system that, among

other things, maps its environment (Ex1006, 6:26–36), associates different cleaning functions with different positions (Ex1006, 6:37–7:6), and navigates itself back to its home base using fiducial markers (Ex1006, 1:14–55). A functional diagram of the robot of Fong is depicted in Fig. 3, reproduced below.

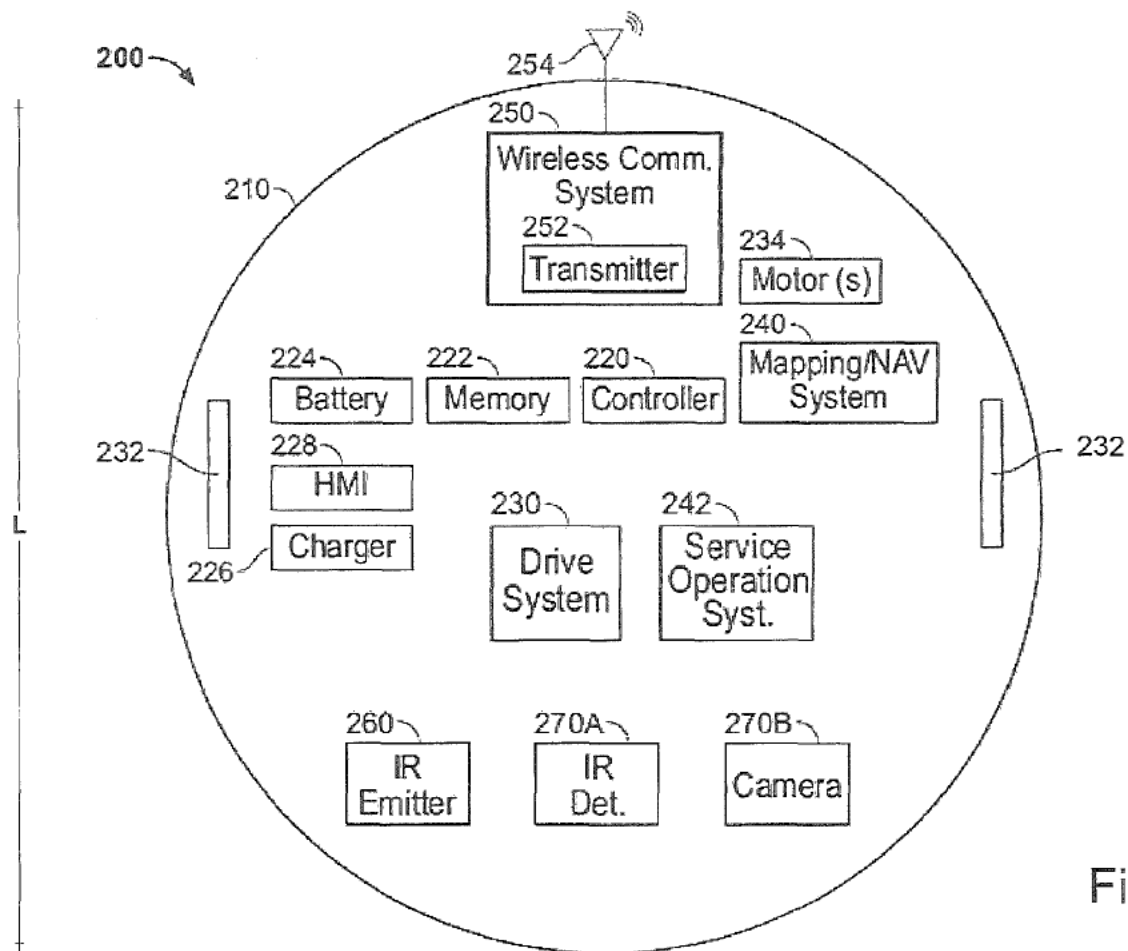


Fig. 3

Ex1006, Fig. 3.

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

73. U.S. Patent No. 9,020,637 (“Schnittman”), titled “Simultaneous Localization and Mapping For a Mobile Robot,” was filed on March 8, 2013,

published on May 8, 2014, and issued on April 28, 2015. It claims priority to US Provisional Application No. 61/721,886, filed on November 2, 2012. It was assigned to iRobot Corporation and relates to simultaneous localization and mapping (SLAM) for mobile robots. Ex1007, (54), (73), 1:14–15.

74. Schnittman discloses a mobile robot configured to autonomously map and navigate an environment using a method that implements ray-tracing. Ex1007, 1:34–54, 2:29–56, 2:57–3:14, 3:50–64. Schnittman explains that he employs a SLAM method 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, 3:50–53. Schnittman depicts the role of ray tracing in its mapping method in FIG. 11 (reproduced below).

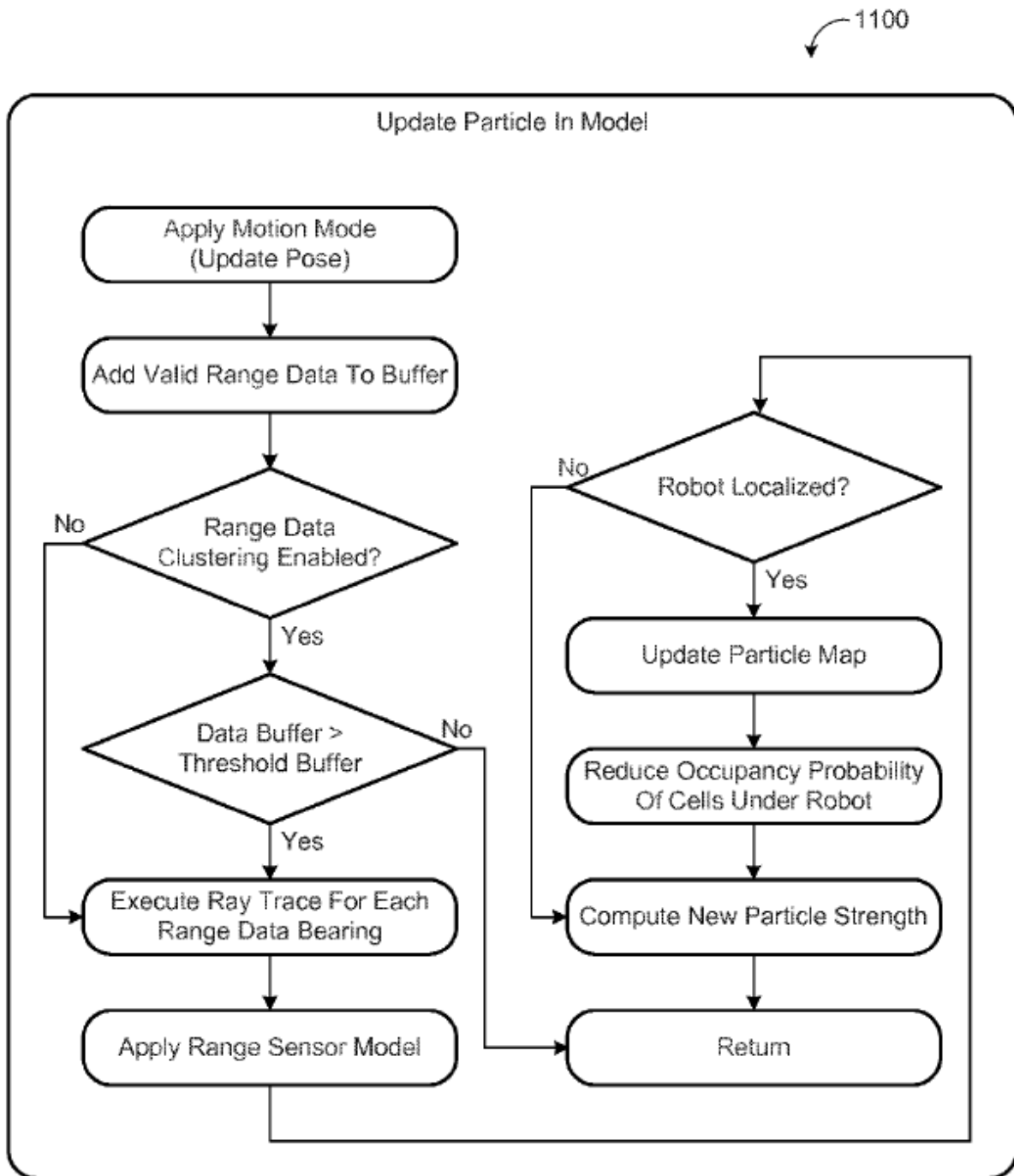


FIG. 11

Ex1007, FIG. 11.

VII. ANALYSIS OF THE CHALLENGED CLAIMS AGAINST THE PRIOR ART

75. Based upon my review of the prior art, particularly the references detailed in this declaration, it is my opinion that the subject matter of each of the Challenged Claims would have been obvious to one of ordinary skill in the art in view of the known prior art references.

76. It is my understanding that each of the prior art references analyzed in this declaration meets the legal requirements for prior art to the '325 patent. I have performed my analysis with this understanding.

77. Based upon my analysis, it is my opinion that the Challenged Claims of the '325 patent are anticipated or rendered obvious by the following prior art grounds:

Ground	Claims	Basis for Rejection
1	1—18	Anticipation by Olson
2	1—18	Anticipation by Stachniss
3	1—18	Obviousness over Olson in combination with Fong
4	1—18	Obviousness over Stachniss in combination with Fong
5	1—18	Obviousness over Olson in combination with Schnittman
6	1—18	Obviousness over Stachniss in combination with Schnittman

78. Unless specifically noted otherwise below, I have accorded claim terms their ordinary and customary meaning as understood by a POSITA and in light of the patent specification and prosecution history.

A. Ground 1: Claims 1—18 are Anticipated by Olson

79. In my opinion, claims 1–18 of the '325 patent are anticipated by Olson. Further, claims 1–18 are rendered obvious by Olson.

1. Element-by-Element Analysis

a) Element 1[pre]: A method of generating a map by a robot, comprising:

80. To the extent the preamble is limiting, it is my opinion that Olson discloses it.

81. Olson discloses a method that allows a robot, with the use of sensors, to generate a map as it travels along a route in an environment. Ex1004, 11–12, 109–10, 113–14, Figures A-1, A-5 (reproduced below). Olson discloses a robot that moves through an environment while simultaneously mapping the environment. Ex1004, 3, 8–12, 43–49, 97, 105–06, 109, 113–14. Olson also discloses a SLAM method for traveling a robot along a route by efficiently constructing accurate maps that are robust to noisy sensor measurements and to ambiguity in the collected data. Ex1004, 3, 17. Olson discloses that “locally accurate maps are critical to collision avoidance, while [accurate] large-scale maps (accurate metrically and topologically) are necessary for efficient route planning.” Ex1004, 3. Specifically, Olson states

that “[m]any basic robot capabilities, such as collision avoidance and path planning depend on a map of the environment. Consequently, map building is a critical component of almost every autonomous robot, particularly if they must operate in unfamiliar environments.” Ex1004, 9. Olson discloses that “[w]hen a robot obtains new information about the environment, this information must be rapidly incorporated into the model of the world [(e.g., map)] so that the robot’s obstacle avoidance and path planning activities can take this information into account.” Ex1004, 89. Olson’s method provides efficient and accurate map building by means of an “incremental optimization [which] allows new information (nodes and edges) to be added to a pose graph, and provides for an efficient incremental update of the posterior map.” Ex1004, 89.

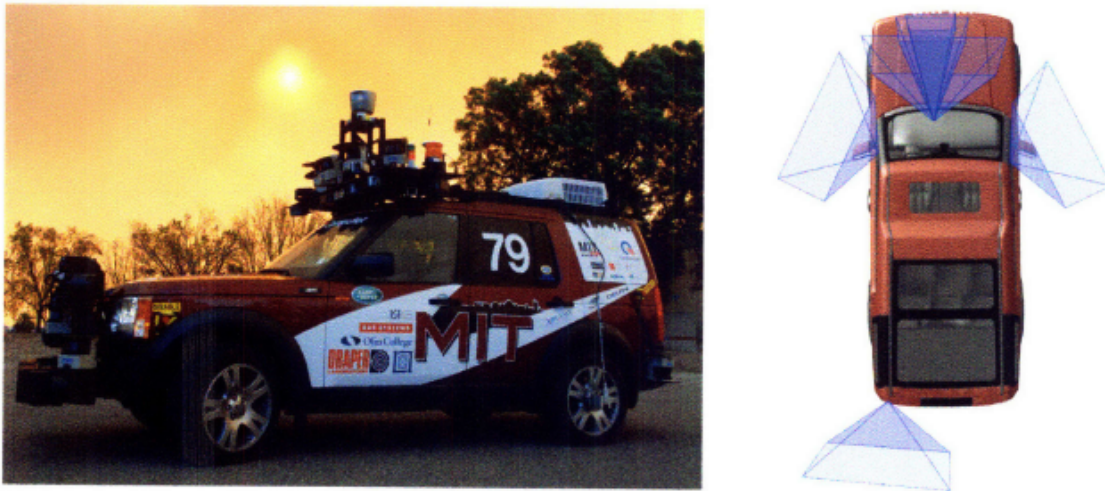


Figure A-1: Talos. Our vision test-bed was MIT’s DARPA Grand Challenge vehicle. The vehicle has five cameras (two forward, left, right, rear), and a high-quality IMU/GPS system for both dead-reckoning and ground-truthing.

Ex1004, Figure A-1.



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

Ex1004, Figure A-5.

82. The robot collects sensor measurements regarding the robot's position called poses and those poses are connected by edges. Ex1004, 15. Olson discloses sensors, including cameras, laser scans, wireless radio frequencies, radars, lidars, inertial measurement unit, and global position systems. Ex1004, 14, 16, 23, 32, 34.

With respect to such sensors, Olson states:

The position of the robot at a particular point in time can be represented as a node in the graph. These types of nodes are known as *poses*. Features (or landmarks) in the environment can also be represented as nodes in the graph: when sensors detect a landmark, the sensor observation is represented as an edge connecting the landmark to the pose from which the observation was made.

Ex1004, 15.

83. Olson discloses that the nodes are combined into a Pose/Feature graph, as illustrated in Figure 1-4 (reproduced below). Ex1004, 15, 19–24, Figure 1-4, Figure 2-1.

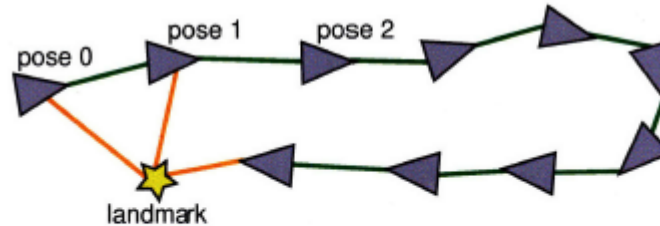


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

84. These poses and landmarks correspond to the environment, and are used to generate a map that depicts the environment. Ex1004, 11–17 (“the map building problem can be formally represented as a non-linear optimization: compute the map that is most consistent with all of the disambiguated sensor data.”).

85. Olson discloses multiple examples of Pose/Feature graphs, such as a map of the Intel Research Center (IRC) dataset, depicted in Figure 3-17 (reproduced below). Ex1004, 43–53, Figure 3-17.

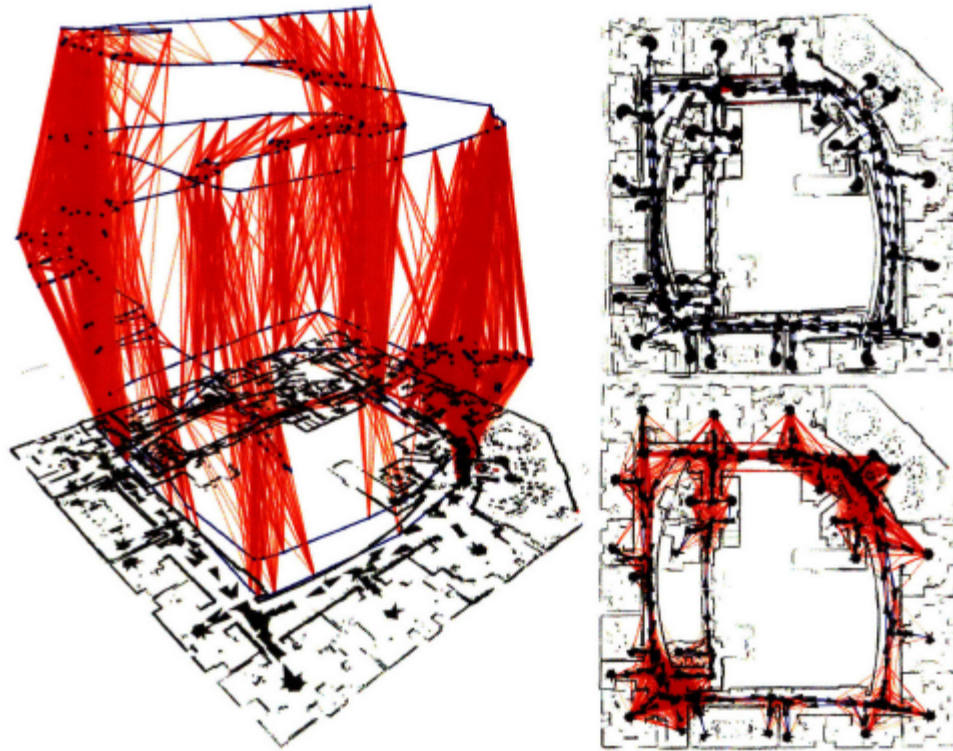


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

86. Therefore, it is my opinion that Olson discloses this limitation.

b) Element 1[a]: traveling, by the robot, in an environment;

87. It is my opinion that Olson discloses this limitation.

88. As discussed above for Element 1[pre] (*see supra* Section VII.A.1.a), Olson discloses a robot that moves through an environment while simultaneously mapping the environment. Ex1004, 3, 8–12, 43–49, 97, 105–06, 109, 113–14; *see also* § VII.A.1.a. This is the same as the '325 patent, which describes a robot that can be operated to or can autonomously move along a desired route. Ex1001, 6:1–

13. Olson also discloses a SLAM system for traveling a robot along a route by efficiently constructing accurate maps that are robust to noisy sensor measurements and to ambiguity in the collected data. Ex1004, 3, 17. Olson discloses that “locally accurate maps are critical to collision avoidance, while [accurate] large-scale maps (accurate metrically and topologically) are necessary for efficient route planning.” Ex1004, 3.

89. The robot collects sensor measurements regarding the robot’s position called poses and those poses are connected by edges. Ex1004, 15. Specifically, Olson states:

The position of the robot at a particular point in time can be represented as a node in the graph. These types of nodes are known as *poses*. Features (or landmarks) in the environment can also be represented as nodes in the graph: when sensors detect a landmark, the sensor observation is represented as an edge connecting the landmark to the pose from which the observation was made.

Ex1004, 15.

90. A POSITA would have understood that a sequence of poses would represent a route that is being travelled by the robot in an environment, and thus the generated map would include information about the robot’s location and position in the environment along the robot’s traveled route.

91. Therefore, it is my opinion that Olson discloses this limitation.

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;

92. It is my opinion that Olson discloses this limitation.

93. As discussed above for Elements 1[pre] and 1[a] (*see supra* Sections VII.A.1.a-b), Olson discloses a method that allows a robot, with the use of sensors, to generate a map as it travels along a route in an environment. Ex1004, 11–12, 109–10, 113–14, Figures A-1, A-5; *see also* §§ VII.A.1.a–b. The robot collects sensor measurements regarding the robot’s position called poses (nodes) and those poses are connected by edges. Ex1004, 15. Specifically, Olson states:

The position of the robot at a particular point in time can be represented as a node in the graph. These types of nodes are known as *poses*. Features (or landmarks) in the environment can also be represented as nodes in the graph: when sensors detect a landmark, the sensor observation is represented as an edge connecting the landmark to the pose from which the observation was made.

Ex1004, 15.

94. A POSITA would have understood that a pose (robot’s position) node in the graph corresponds to a sensor observation (claimed “scan generated by a sensor of the robot”) at that “pose from which the [sensor] observation was made.” (claimed “location in the environment”).

95. Olson discloses that the nodes are combined into a Pose/Feature graph, as illustrated in Figure 1-4 (reproduced below). Ex1004, 15, 19–24, Figure 1-4, Figure 2-1.

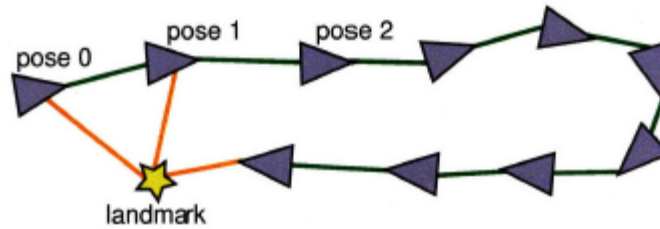


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

96. Olson further discloses that the map is generated by taking measurements (claimed “scan generated by a sensor”) at a plurality of poses, which may be collected into a pose graph wherein the poses are represented as nodes in the graph (claimed “respective node of the plurality of nodes corresponds to a scan generated by a sensor of the robot at a location in the environment”). For example, Olson states that:

Sensors observe the environment relative to the robot's current position, and the noise contaminating these robot-relative observations is independent. Projecting these observations into a global coordinate frame requires only the knowledge of the robot's position. In other words, sensor observations (in the global coordinate frame) are conditionally independent given the robot trajectory. This is the key insight behind FastSLAM, as it allows the posterior distribution to be factored into terms corresponding to the robot trajectory and the individual position of each feature in the environment. . . .

Ex1004, 12.

97. Further, “[w]hen sensors detect a landmark, the sensor observation is represented as an edge connecting the landmark, to the pose [represented as a pose-

node] from which the observation was made.” Ex1004, 15. These nodes are combined into a Pose/Feature graph, such as in Figure 1-4 (reproduced above). Ex1004, 15, 19–24, Figure 1-4, Figure 2-1; *see also* Ex1004, Figure 1-2.

98. These poses and landmarks correspond to the environment, resulting in a map that depicts the environment. Ex1004, 11–17 (“the map building problem can be formally represented as a non-linear optimization: compute the map that is most consistent with all of the disambiguated sensor data.”).

99. Olson discloses multiple examples of Pose/Feature graphs, such as a map of the Intel Research Center (IRC) dataset, depicted in Figure 3-17 (reproduced below). Ex1004, 43–53, Figure 3-17.

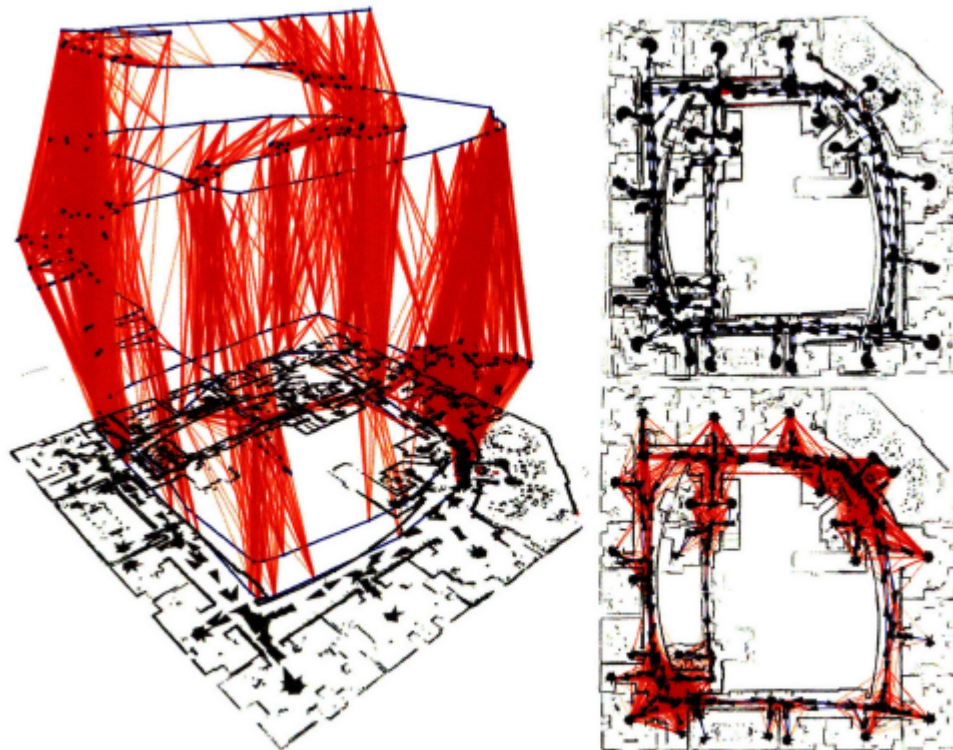


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

100. This map includes data regarding features of the Intel Research Center, including the walls, doors and the robot's locations and positions along its traveled route. *See also* Ex1004, 49 (describing the IRC dataset). Olson further discloses that its system can generate such a map by “incorporating observations one at a time (and outputting a posterior map after every observation).” Ex1004, 100–01, Figure 5-4.

101. Therefore, it is my opinion that Olson discloses this limitation.

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

102. It is my opinion that Olson discloses this limitation.

103. Olson discloses that “[s]can matching is the process of finding a rigid-body transformation that improves the alignment of two scans. Incremental scan matching is the special case of examining temporally-consecutive scans: it is used to enhance or replace conventional odometry sensors.” Ex1004, 116–17, 119–20, Figure A-9 (reproduced below).

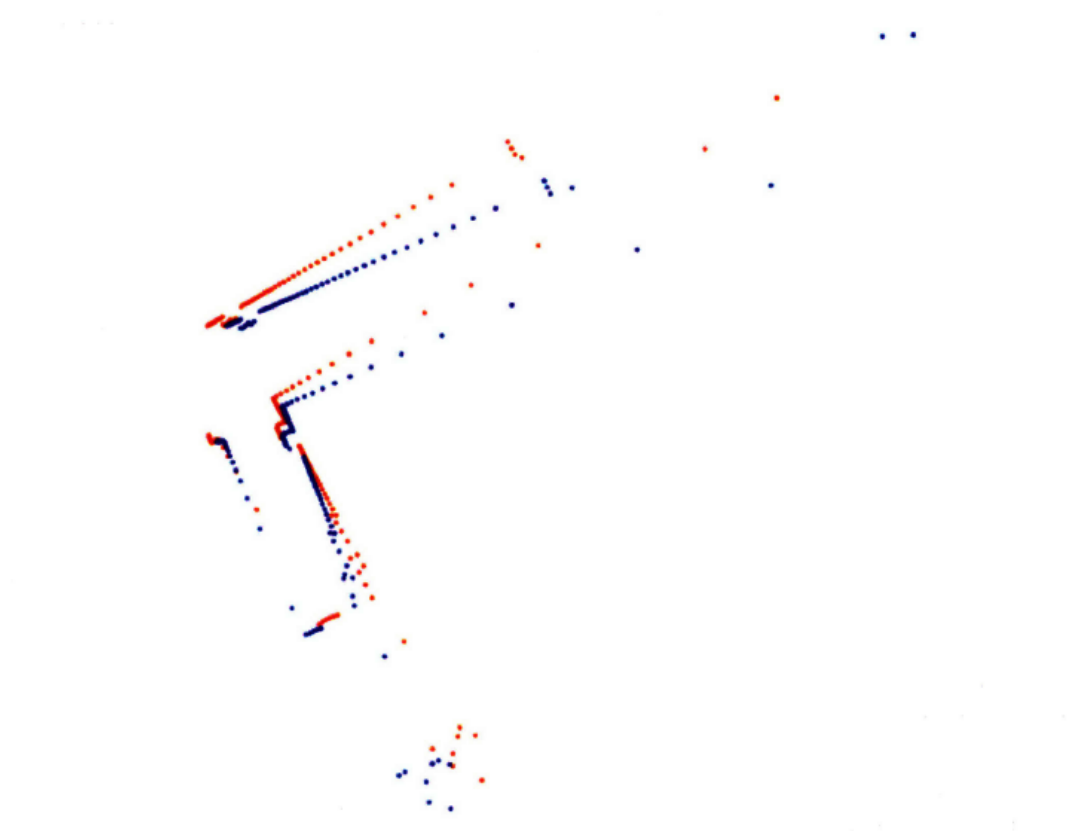


Figure A-9: Scan Matching. Two scans taken 133 ms apart are poorly aligned. Scan-matching is the process of finding a rigid-body transformation that improves the alignment of two scans. This alignment corresponds to the motion of the robot.

Ex1004, Fig. A-9.

104. Olson further explains that scan matching may be performed using camera data or laser range data, though the specific method for performing scan matching varies according to the data available. Ex1004, 32 (“[C]ameras and lidars, for example, produce very different types of data that require different matching algorithms.”). For example, Olson explains that scan matching between camera images proceeds by extracting features, e.g., via SIFT, matching them between images, e.g., using SIFT feature descriptors, and finding from the two sets of

matching features the best rigid-body transform, e.g., using RANSAC. Ex1004, 34–36, 44–46, 110–13, Figures 3-8 and 3-9 (reproduced below).

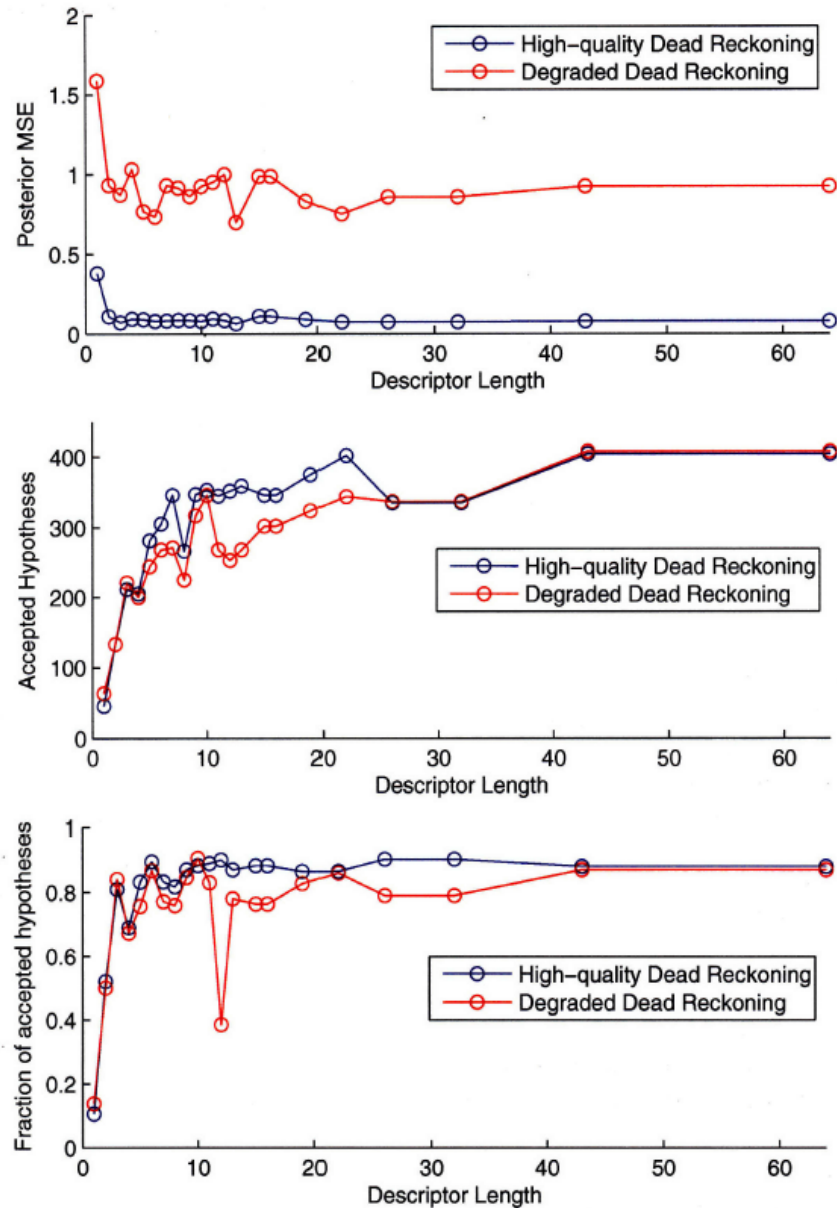


Figure 3-8: Area C Robustness. Shorter SIFT descriptors present greater perceptual ambiguity, and are more likely to produce incorrect matches. However, our method produces good maps in each case, and most surprisingly, can do almost as well with 3-dimensional vectors as with 128-dimensional vectors. The downward blip at $x = 12$ (bottom) was due to an unusually large number of ambiguous hypothesis sets, in which the ratio of the first to second eigenvalues was less than the threshold of 2.0.

Ex1004, Figure 3-8.

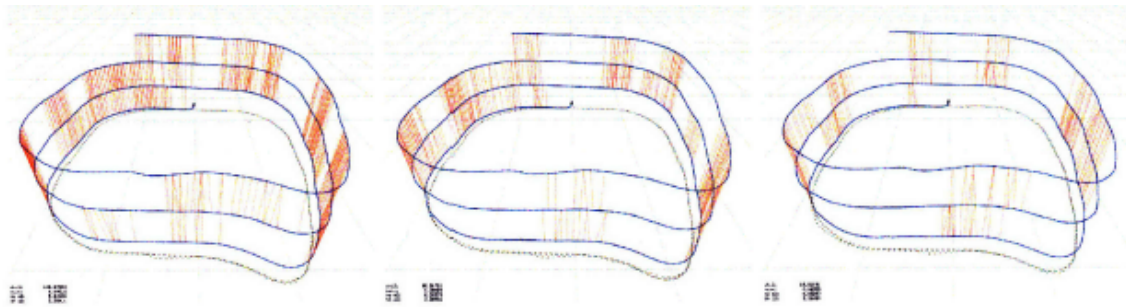


Figure 3-9: Area C Pose Graphs versus Descriptor Length. The pose/feature graph for the Area C dataset using 128-dimensional descriptors, 8-dimensional descriptors, and 1-dimensional descriptors. As the size of the descriptor goes down, ambiguity increases, resulting in fewer loop closures (red lines).

Ex1004, Figure 3-9.

105. Olson explains that scan matching between laser scans proceeds by extracting and matching features, such as corners and contours. Ex1004, 116–22. Olson depicts examples of scan matching using laser scans in Figures A-9 and A-10, reproduced below.

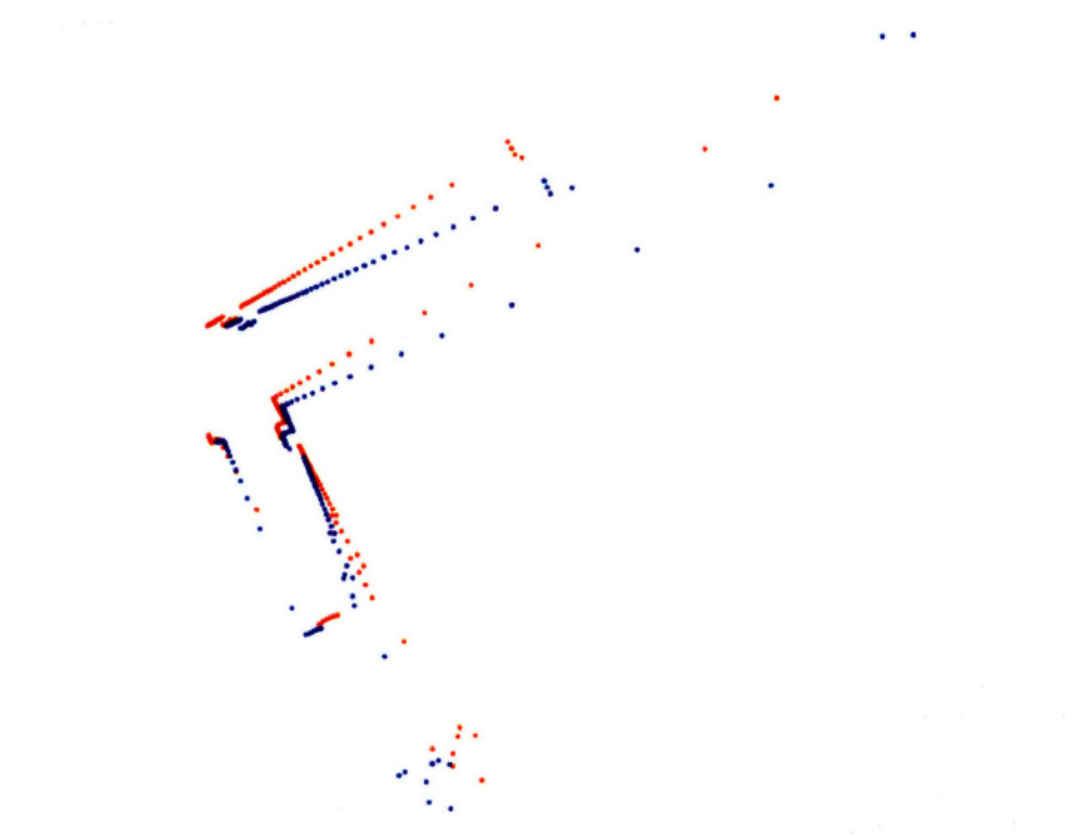


Figure A-9: Scan Matching. Two scans taken 133 ms apart are poorly aligned. Scan-matching is the process of finding a rigid-body transformation that improves the alignment of two scans. This alignment corresponds to the motion of the robot.

Ex1004, Figure A-09.

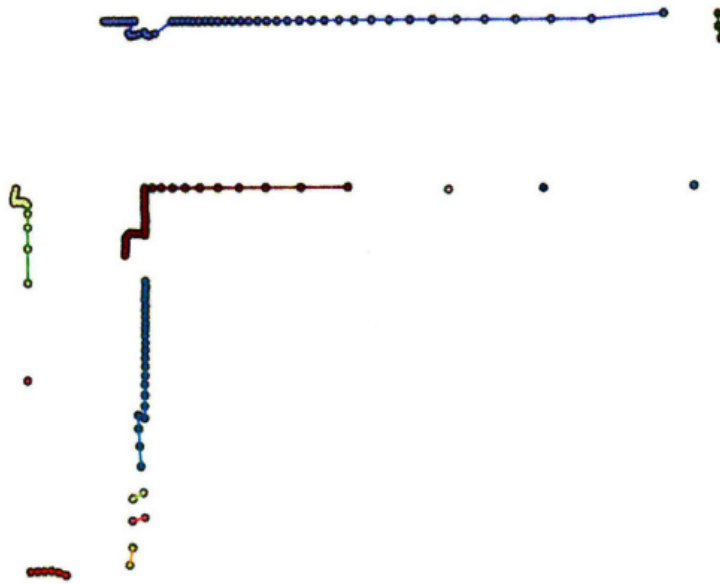


Figure A-10: Contour Extraction. A laser scanner measures only a discrete set of points; it is necessary to infer the *contours* of the surface being sampled as shown here.

Ex1004, Figure A-10.

106. Olson further discloses that it performs scan matching on extended scan groups. For example, Olson discloses “[t]he robot trajectory was estimated via incremental scan matching and loop closure hypotheses generated using a combination of local feature matching and scan matching refinement.” Ex1004, 46. Olson further explains that “[i]ncremental scan matching is the special case of examining *temporally-consecutive scans*” (claimed “extended scan groups being determined in-part on at least two or more nodes of the plurality of nodes”). Ex1004, 116–17, 119–20, Figure A-9.

107. Olson also discloses that “to decrease their error rate, data association [(scan matching)] algorithms typically perform association on *groups of*

observations [(sensor scans)] at once.” (claimed “extended scan groups”). Ex1004, 30.

108. Olson further discloses that “[t]he first step [] is to identify those poses that might contain overlapping sensor readings.” Ex1004, 32. Olson explains that “[g]iven a pose [node] *a*, we wish to find ***all other poses [(pose nodes)] in the graph whose sensor readings might overlap those from pose [node] a***” (claimed “extended scan groups”). Ex1004, 32. Further, Olson discloses that “we must know the sensor range in order to determine two sensor scans might overlap: large sensor ranges make it more likely that ***nodes will have overlapping fields of view***” (claimed “extended scan groups”). Ex1004, 33–34.

109. For example, as Olson says in its “Method Overview” for “Loop Closing:”

*Our loop-closing algorithm operates in several stages. We first generate a number of hypotheses. **Given two robot positions (at different points in time) [at least two or more nodes of the plurality of nodes]**, we can estimate the probability that **those two positions are close enough together for them to have observed the same [or overlapping] environmental features [(extended scan groups)]**. If so, we attempt to generate a hypotheses relating the position of those poses. The particular hypothesis-generation algorithm varies according to the types of sensors being used: cameras and lidars, for example, produce very different types of data that require different matching algorithms.*

Ex1004, 32.

110. Therefore, it is my opinion that Olson discloses this limitation.

- 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.**

111. In my opinion. Olson discloses this limitation.

112. For example, Olson discloses a method that implements “loop closing.”

Specifically,

The term “loop closing” arises from the common case where a robot drives in a large loop, *returning to its starting point* [start location and the end location being at a substantially similar location in the environment]. If, after travelling around the loop, the robot can recognize that it is at its starting position, it “closes” the loop, creating a geometric relationship between the first and last position of the robot. This geometric relationship has two major effects:

- It establishes a *topological* relationship between temporally distant parts of the robot’s trajectory. The robot can use this new topological link as a “short-cut” when planning routes.
- It provides a *metrical* relationship between the beginning and end of the robot’s trajectory that can be used to refine the estimate of the robot’s trajectory, improving upon the estimate provided by dead-reckoning.

...

Loop closing is related to place recognition, which has applications beyond path planning and map building. For example, the same algorithms could be used by a robot to find a recharging station and properly align itself to it.

Ex1004, 13–14. *See also* Ex1004, 60-61, 94, 97–98, 100–03.

113. Loop closing allows the robot to adjust its location at the end node to be the same as the starting node, which then allows for all the nodes to be adjusted (constraining the graph between a start location and an end location). Ex1004, 60–61, Figure 4-1. For example, Olson depicts a simple loop closure in Figure 4-1

(reproduced below). The red arrows signify the adjustments to conform the starting position to the ending position. Ex1004, 60.

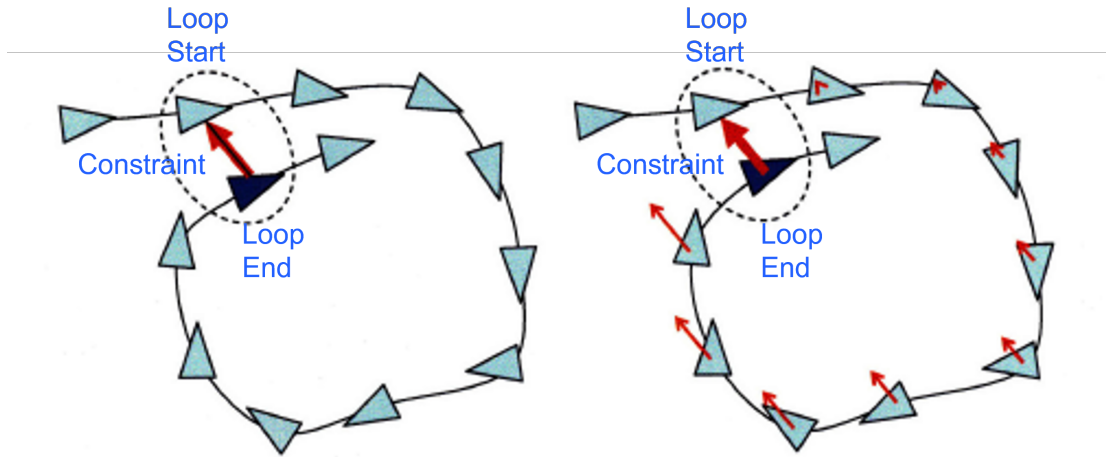


Figure 4-1: Map Optimization Intuition. The χ^2 error of a graph with a poorly-satisfied constraint (left, red arrow) can be reduced by distributing small adjustments around the nodes in the loop (right).

Ex1004, Figure 4-1 (annotated).

114. Olson also provides a real practical example for the Intel Research Center dataset, as illustrated in Figure 5-4 (reproduced below).

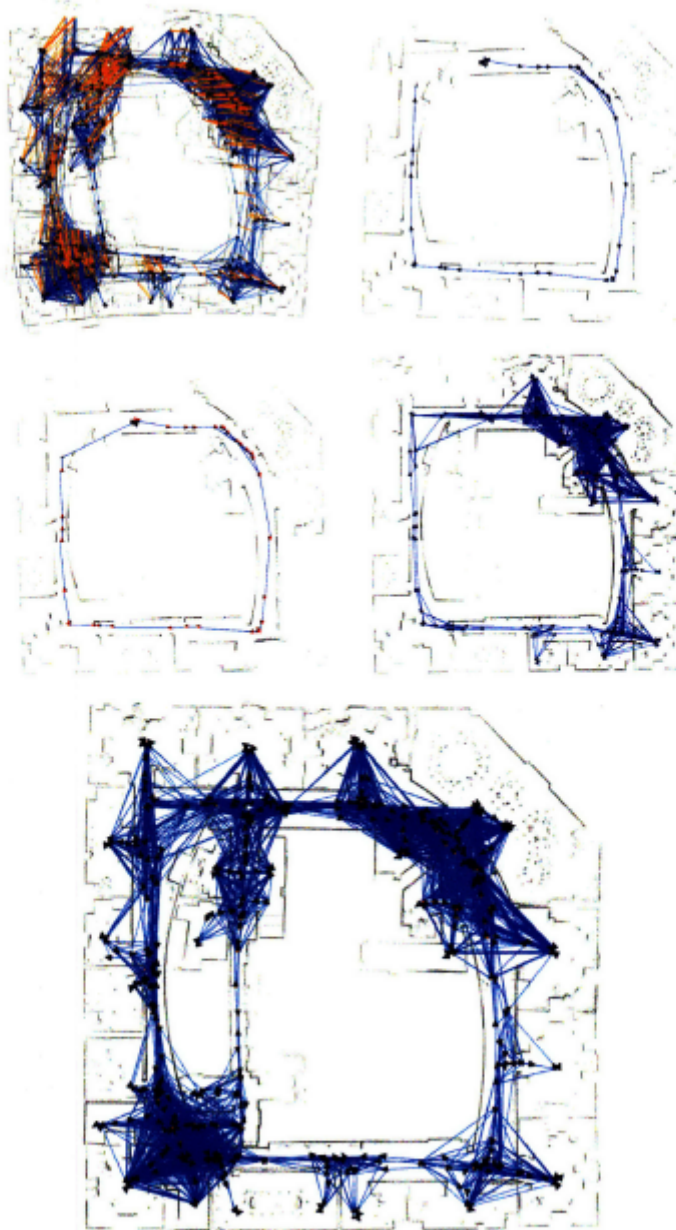


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

115. Therefore, it is my opinion that Olson discloses this limitation.

- 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;

116. In my opinion, Olson discloses this limitation.

117. For example, Olson discloses that each of the poses (possible locations) in the Pose/Feature graph comprises a range based on confidence measure. Olson discloses that “[i]n general terms, the map building problem can be described as finding the posterior probability distribution function of a map x given a set of sensor data z and a set of commanded robot motions u .” Ex1004, 12–13. Olson further discloses that the map comprises “the trajectory of the robot s sampled at discrete times [(sequence of robot’s locations represented by pose nodes in the pose/feature graph)], and the location of other features f in the environment.” Ex1004, 12. Olson discloses that “[t]he nodes of a pose/feature graph are the same as the random variables of a graphical model.” Ex1004, 20. A POSITA would have understood that a random variable is represented using a probability distribution, as also taught by Olson. Ex1004, 12–13, 19, 22. Olson discloses that “uncertainty can be represented as a probability distribution” and that each node in the graph has an associated probability distribution representing a range (e.g., an uncertainty ellipse-shaped or circular region surrounding each node). Ex1004, 12–13, 22 (disclosing “uncertainty can be represented as a probability distribution”), 32 (disclosing that uncertainty can be measured using “the area of the covariance ellipse, and is thus proportional to the area of the region in which pose [node] b is likely to be found

given the position of pose [node] a .”), 118 (disclosing “range uncertainty” and “probability distributions resemble radially-oriented ellipses ... [and] [i]n practice, [can be] approximate[d] as a circle”).

118. Olson further indicates that “the goal is to estimate the positions of all the nodes (the state variables).” Ex1004, 16. Olson discloses that the information matrix, which is expressed in terms of the inverse covariance matrix Σ^{-1} , “estimates the relative confidence of each node.” Ex1004, 66. Olson further discloses that, given a current state estimate (e.g., position estimate) of a node and associated confidence measure (e.g., as given by the information matrix or inverse covariance matrix Σ^{-1}), a range d corresponding to a distance from the current state estimate (e.g., current estimated position of a node) can be computed by minimizing an error incorporating the confidence measure. Ex1004, 23–24, 63–66. Olson further discloses that such error may be represented by the chi-squared (χ^2) error. Ex1004, 23–24, 63–66. Additionally, for a given d (corresponding to a distance from the current position estimate of a node), the corresponding error (e.g., χ^2 error) can be computed. Ex1004, 23–24, 63.

119. A POSITA would consider these to disclose computing ranges as taught by the '325 patent, which explains that ranges can be computed “using a posterior probability distribution,” or using “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.

120. Olson further discloses that these ranges are based on scan-matching. For example, Olson discloses that the robot's poses (possible locations and their associated ranges as explained in ¶¶ 117–119 *supra*) are estimated based on scan matching. For example, Olson discloses "[t]he robot trajectory [(sequence of poses)] was estimated via incremental scan matching and loop closure hypotheses generated using a combination of local feature matching and scan matching refinement." Ex1004, 46; *see also* § VII.A.1.d.

121. Olson further discloses that "[t]he first step in identifying loop closure hypotheses is to identify those poses that might contain ***overlapping sensor readings***," the overlap being determined via scan matching. Ex1004, 32. Olson explains that "[g]iven a pose [node] *a*, we wish to find ***all other pose[] [nodes] in the graph whose sensor readings might overlap those from pose [node] a***". Ex1004, 32. Further, Olson disclose "we must know the sensor range [at a robot's estimated location (pose node)] in order to determine whether two sensor scans might overlap: large sensor ranges make it more likely that ***nodes will have overlapping fields of view***." Ex1004, 33–34. A POSITA would have understood that the overlap between sensor readings at robot's possible locations (corresponding

to robot's poses and associated ranges) can be determined via scan matching, as disclosed by Olson.

122. For example, as Olson says in its "Method Overview" for "Loop Closing:"

*Our loop-closing algorithm operates in several stages. We first generate a number of hypotheses. **Given two robot positions (at different points in time), we can estimate the probability that those two positions are close enough together for them to have observed the same [or overlapping] environmental features** [(matching scans)]. If so, we attempt to generate a hypotheses relating the position of those poses. The particular hypothesis-generation algorithm varies according to the types of sensors being used: cameras and lidars, for example, produce very different types of data that require different **matching algorithms**.*

Ex1004, 32.

123. Olson further explains that the hypotheses generated capture uncertainty (range) information related to the position of the node. Specifically,

We estimate the **relative positional uncertainty** [range] between nodes a and b by searching for the minimum-uncertainty path through the pose/feature graph that connects them. This path can be found by using variant of Dijkstra's Algorithm [55]:

In order to compare the uncertainty of two paths, we use the determinant of the paths' covariance matrices. **Geometrically, the determinant can be interpreted as the area of the covariance ellipse, and is thus proportional to the area of the region in which pose b is likely to be found given the position of pose a.** Larger search areas generally result in more computational effort. Consequently, picking the path with the smaller determinant generally minimizes the amount of computation needed to find pose b.

Ex1004, 32.

124. Therefore, it is my opinion that Olson discloses this limitation.

g) Element 2[b]: determining confidences associated with a respective one of the range of possible locations;

125. In my opinion, Olson discloses this limitation. As explained in Section VII.A.1.f, Olson discloses determining confidences associated with a range of possible locations.

126. Olson discloses that “[t]he nodes of a pose/feature graph are the same as the random variables of a graphical model.” Ex1004, 20. A POSITA would have understood that a random variable is represented using a probability distribution providing a range of possible values and a confidence measure associated with that range, as also taught by Olson. Ex1004, 12–13, 19, 22. Olson discloses that “uncertainty can be represented as a probability distribution” and that each node in the graph (random variable) has an associated probability distribution representing a confidence region (e.g., an uncertainty ellipse-shaped or circular region surrounding each node). Ex1004, 12–13, 22 (disclosing “uncertainty can be represented as a probability distribution”), 32 (disclosing that uncertainty can be measured using “the area of the covariance ellipse, and is thus proportional to the area of the region in which pose [node] *b* is likely to be found given the position of pose [node] *a*.”), 118 (disclosing “range uncertainty” and “probability distributions

resemble radially-oriented ellipses ... [and] [i]n practice, [can be] approximate[d] as a circle”).

127. Olson further discloses that “the goal is to estimate the positions of all the nodes (the state variables).” Ex1004, 16. Olson discloses that the information matrix, which is expressed in terms of the inverse covariance matrix Σ^{-1} , “estimates the relative confidence of each node.” Ex1004, 66. Olson further discloses that, given a current state estimate (e.g., position estimate) of a node and associated confidence measure (e.g., as given by the information matrix or inverse covariance matrix Σ^{-1}), a range d corresponding to a distance from the current state estimate (e.g., current estimated position of a node) can be computed by minimizing an error incorporating the confidence measure. Ex1004, 23–24, 63–66. Olson further discloses that such error may be represented by the chi-squared (χ^2) error. Ex1004, 23–24, 63–66. Additionally, for a given d (corresponding to a distance from the current position estimate of a node), the corresponding error (e.g., χ^2 error) can be computed. Ex1004, 23–24, 63.

128. Olson further discloses that “**confidence** is the inverse of the covariance matrix,” Σ^{-1} . Ex1004, 23. Olson also discloses that it tracks “the **confidence** of each individual node.” Ex1004, 72.

129. A POSITA would have understood these to disclose computing ranges and determining confidences associated with these ranges as taught by the ’325

patent, which explains that the confidences described are statistical measures related to the likely position of the pose-node. For example, the '325 Patent explains, “[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.

130. Therefore, it is my opinion that Olson discloses this limitation.

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

131. In my opinion, Olson discloses this limitation.

132. For example, Olson discloses that its method generates a map by optimizing the estimated positions of the nodes in its graph. Ex1004, 3 (“Building accurate maps can be case as an optimization problem: find the map that is the most probable given the set of observations of the environment. . . . This thesis describes an optimization algorithm that can rapidly estimate the maximum likelihood map given a set of observations”), 12 (“In general terms, the map building problem can be described as finding the posterior probability distribution function of a map x .”), 15–17. Olson explains that this graph optimization finds the location of the plurality of nodes. Ex1004, 16 (“The pose graph encodes a non-linear optimization problem: the goal is to *estimate the position of all the nodes* (the state variables) such that the

constraints have the minimum possible error.”). Olson depicts the results of its optimization method for the Intel Research Center in Figure 3-17, reproduced below.

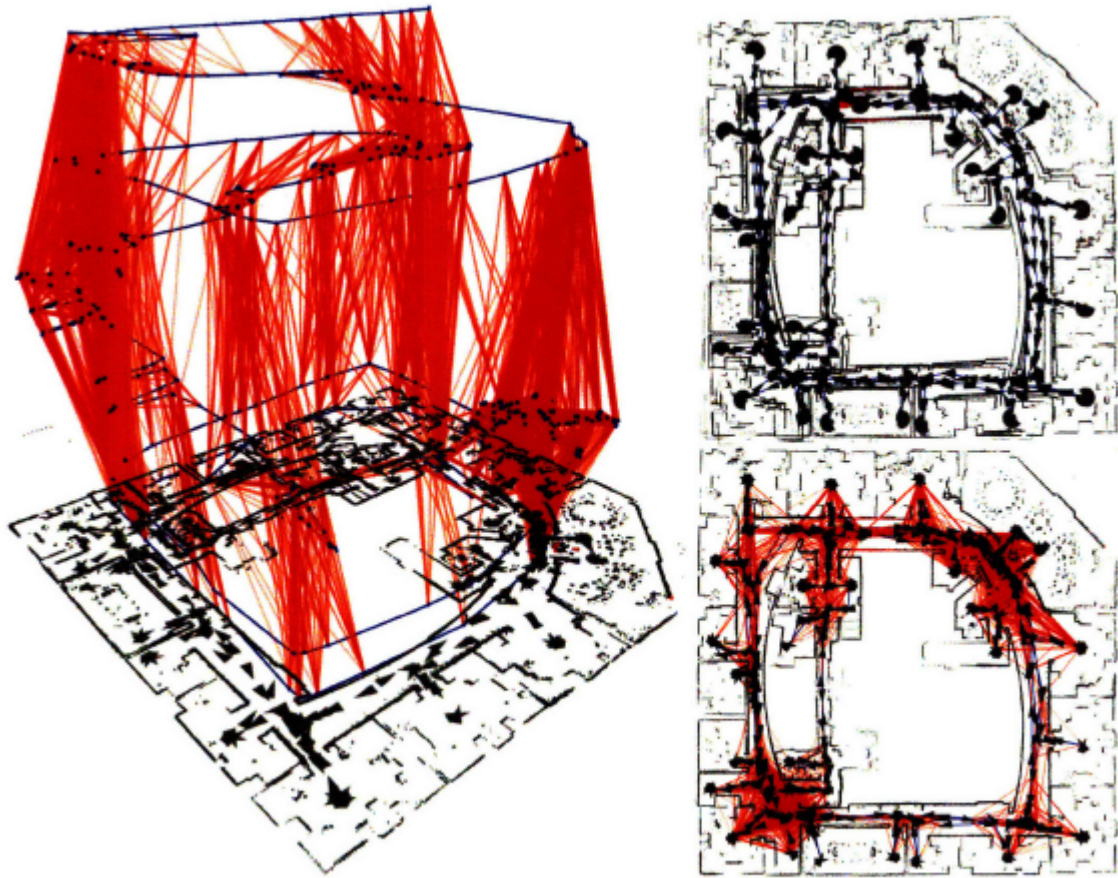


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

133. Olson further discloses that its optimization method is based at least in-part on the confidences. Olson explains that its optimization method uses a “hybrid” approach implementing both non-linear least-squares and stochastic gradient descent, both of which rely on confidences. Ex1004, 63–64 (non-linear least

squares), 64–65 (stochastic gradient descent), 65–66 (“Our Hybrid Model”). Olson depicts this method in Algorithm 7, reproduced below. Ex1004, 71–72.

Algorithm 7 SGD-Optimize-Graph

```

1:  $\lambda = 1/3$ 
2: repeat Optimize the graph
3:   Randomly permute order of Constraints
4:   {Update approximation  $M = J^T \Sigma^{-1} J$ . Let  $M_i$  be the  $i^{th}$  diagonal block.}
5:   for all  $\{a, b, t_{ab}, \Sigma_{ab}\}$  in Constraints do
6:     compute  $R$  using Eqn. 4.15
7:      $W = R^T \Sigma_{ab}^{-1} R$ 
8:     for all  $i \in [a + 1, b]$  do
9:        $M_i = M_i + W$ 
10:    Update error-distribution trees with  $M$ 
11:  end for
12: end for
13:  $\Gamma = \max(\Sigma_i^{-1})$ 
14:
15: {Modified Stochastic Gradient Descent}
16: for all  $\{a, b, t_{ab}, \Sigma_{ab}\}$  in Constraints do
17:    $r = X_a^{-1} \oplus X_b$ 
18:    $r(3) = \text{mod2pi}(r(3))$ 
19:   compute  $R$  using Eqn. 4.15
20:    $s = -(b - a) \lambda R^T \Gamma^{-1} \Sigma_{ab}^{-1} r$ 
21:    $s_{max} = X_b - (X_a \oplus T_{ab})$ 
22:    $s = \text{clamp}(s, s_{max})$ 
23:   distribute( $a + 1, b, s$ )
24: end for
25:    $\lambda = \lambda / (\lambda + 1)$ 
26: until converged

```

Correction based on the
Confidences of the
plurality of nodes

Correction based on the
Confidences of the
plurality of nodes

Ex1004, Algorithm 7 (annotated).

134. Further, as described above with respect to Elements 2[a] and 2[b] (*see supra* Sections VII.A.1.f–g), Olson 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 algorithm is to reduce χ^2 error.” Ex1004, 16, 94. Olson further discloses that this can be accomplished by computing a “value d represent[ing] a change in the state variable (position of node) that will minimize the χ^2 error” incorporating the confidence measure. Ex1004, 24; *see also* Ex1004, 63–66.

135. Therefore, it is my opinion that Olson discloses this limitation.

- 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.**

136. In my opinion, Olson discloses this limitation.

137. As discussed above with respect to Element 2[c] (*see supra* Section VII.A.1.h), Olson discloses generating a map from the optimized graph. Additionally, as discussed above with respect to Element 1[b] (*see supra* Section VII.A.1.c), sensor scans are associated with the plurality of nodes.

138. Olson further discloses that the generation of the map comprises ray tracing using the scans associated with the plurality of nodes. Ex1004, 34–36, 107, 110–12. For example, Olson explains that it uses scan-matching, which comprises ray-tracing, to generate the map, saying:

Periodically, the measurements for each track are examined to see if the position of the SIFT feature can be determined. Since ***each observation of a feature consists of only a bearing to the feature***, the feature must be observed from several different positions in order to compute its position. ***Each bearing to the feature corresponds to a ray: when the rays from different***

observations intersect, we can estimate of the location of the feature. Once the feature is localized, the track is reset so that the feature can be independently localized again and again. The result of this process is a sequence of independent rigid-body transformations relating the vehicle to the feature.

Ex1004, 34–35.

139. Olson depicts SIFT-based ray-tracing in Figure A-3, reproduced below:

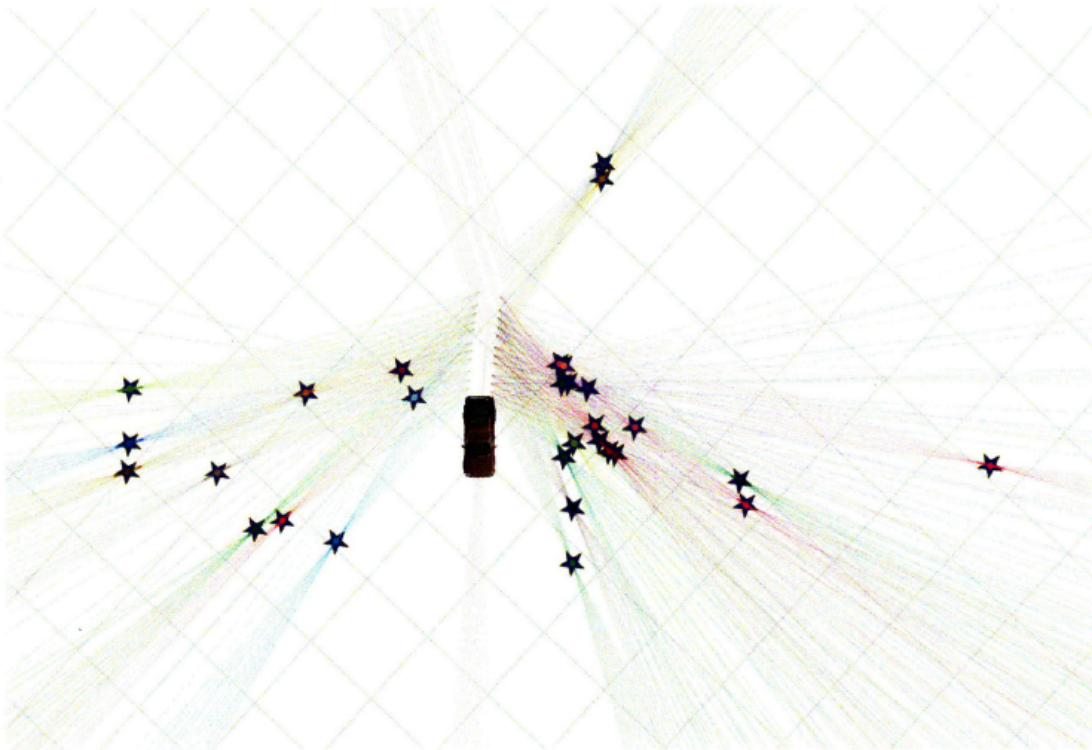


Figure A-3: SIFT Landmark Initialization. Landmarks are computed by tracking SIFT features over short motions of the robot: when the intersection of the bearings converges near a single point, a landmark is initialized.

Ex1004, Figure A-3.

140. As a further example, Olson explains that map-building with laser-scanners also comprises ray-tracing. Ex1004, 117–19. For example, Olson explains:

We wish to determine the cost associated with a particular alignment of one laser scan with another. The noise model of the laser scanner involves uncertainty in both range and bearing. Range is typically more uncertain than bearing, and so the probability distributions resemble radially-oriented ellipses. In other words, the probability distribution of an observed point is dependent upon the position of that point relative to the scanner. In practice, we approximate the distribution as a circle (regardless of its position). Specifically, given a laser scan point (x, y) and the distance d to the nearest contour C, we approximate the probability of a single lidar point as:

$$P(x, y | C) \propto e^{-d^2/\sigma^2} \quad (\text{A.1})$$

...

Laser scanners are strictly line-of-sight, and are susceptible to occlusions. In general, better scan matching results can be obtained by building the cost lookup table using several previous scans. This increases the completeness of the lookup table (and thus the likelihood of getting a good match) at the expense of potentially introducing errors into the lookup table if the alignment of those earlier scans is incorrect.

Ex1004, 117–18.

141. A POSITA would have understood that a mapping procedure based on laser-scans, that uses multiple scans to account for occlusions employs ray-tracing in the same way that the analogous SIFT-based algorithm employs ray-tracing to determine the distance to a landmark based on bearing to the landmark from multiple positions.

142. Therefore, it is my opinion that Olson discloses this limitation.

- 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

143. In my opinion, Olson discloses this limitation. As explained above with respect to Element 2[c] (*see supra* Section VII.A.1.h), Olson discloses optimizing the graph to find a location of the plurality of nodes based at least in-part on the confidences. Olson further discloses that its map-building algorithm comprises generating a cost function based on the relative location of each of the plurality of nodes and the confidences associated with each of the plurality of nodes.

144. For example, Olson explains,

The pose graph encodes a non-linear optimization problem: the goal is to estimate ***the position of all the nodes*** (the state variables) such that the constraints have the ***minimum possible error*** [(confidences associated with each of the plurality of nodes)]. The large number of state variables, the non-linear nature of the constraint equations, and the poor initial estimate (typically derived from dead-reckoning) combine to make the optimization problem difficult. Its importance and difficulty have made optimization a heavily researched topic, but performance on large problems (those with many nodes and edges) remain computationally difficult.

Ex1004, 16.

145. Additionally, Olson discloses:

One way of "capturing" the cumulative nature of robot motion is to represent the robot trajectory as a series of rigid body transformations. In this case, the position of the trajectory node i in the trajectory is the composition of all the rigid-body transformations $T_0 \oplus T_1 \oplus \dots \oplus T_{i-1}$, and the state space is a list of the rigid-body transformations. We call this the "relative" (x_{rel}) state space (see Fig. 4-2)below].

Ex1004, 62.

$$\begin{array}{ccc}
\begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ x_1 \\ y_1 \\ \theta_1 \\ x_2 \\ y_2 \\ \theta_2 \\ \dots \end{bmatrix} & \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ \cos(\theta_0)(x_1 - x_0) + \sin(\theta_0)(y_1 - y_0) \\ -\sin(\theta_0)(x_1 - x_0) + \cos(\theta_0)(y_1 - y_0) \\ \theta_1 - \theta_0 \\ \cos(\theta_1)(x_2 - x_1) + \sin(\theta_1)(y_2 - y_1) \\ -\sin(\theta_1)(x_2 - x_1) + \cos(\theta_1)(y_2 - y_1) \\ \theta_2 - \theta_1 \\ \dots \end{bmatrix} & \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ x_1 - x_0 \\ y_1 - y_0 \\ \theta_1 - \theta_0 \\ x_2 - x_1 \\ y_2 - y_1 \\ \theta_2 - \theta_1 \\ \dots \end{bmatrix} \\
\mathbf{x}_{\text{global}} & \mathbf{x}_{\text{rel}} & \mathbf{x}_{\text{incr}}
\end{array}$$

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.

146. Olson further explains, with respect to laser-scanning methods:

Scan matching is an optimization problem with three free parameters corresponding to the *parameters of a rigid-body transformation* [relative location of each of the plurality of nodes]. For each rigid-body transformation, a *cost function* is computed that indicates the quality of the alignment. An optimization algorithm then attempts to find the minimum-cost alignment [based on confidences]. This section describes these steps.

Ex1004, 116; *see also* Ex1004, 61–63 (disclosing relative positions of nodes are represented using a rigid-body transformation).

147. Further, as explained above with respect to Element 2[b] (*see supra* Sections VII.A.1.h), Olson discloses that “the goal [of the graph optimization] is to estimate the positions of all the nodes (the state variables)” and that “[t]hat a reasonable goal for an optimization algorithm is to reduce χ^2 error [(cost function)].”

Ex1004, 16, 94. Olson further discloses that this can be accomplished by computing

a “value *d represent[ing] a change in the state variable* [relative location of each of the plurality of nodes with respect to an initial location or a previously estimated location] that will minimize the χ^2 error [cost function]” incorporating the confidence (e.g., inverse covariance matrix Σ^{-1}) associated with each of the plurality of nodes. Ex1004, 24; *see also* Ex1004, 63–66. As depicted below, the calculation of *d* relies on the confidence matrix (*i.e.*, the inverse of the covariance matrix), Σ^{-1} , which is a measure of the confidences associated with each of the plurality of nodes.

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

148. Additionally, Olson discloses that map building algorithms “have used state space representations in which *the relative position of nodes is used.*” Ex1004, 60.

149. Therefore, it is my opinion that Olson discloses this limitation.

k) Element 3[b]: solving the cost function for a minimum value.

150. In my opinion, Olson discloses this limitation.

151. As discussed above with respect to Element 2[c] (*see supra* Section VII.A.1.h), Olson generates a map using a hybrid optimization procedure based on non-linear least-squares and stochastic gradient descent. Further, as discussed above with respect to Element 3[a] (*see supra* Section VII.A.1.j), Olson discloses a cost-

function. Olson further discloses that these algorithms solve for a minimum value of the cost function.

152. For example, Olson explains that its method seeks “the maximum likelihood (minimum cost) position of each node.” Ex1004, 16. Olson further explains, “the goal is to estimate the position of all the nodes (the state variables) such that the constraints have the minimum possible error.” Ex1004, 16. Olson explains that its algorithm may compute the minimum error in a batch mode based on all the data that has been collected so far, or incrementally optimize the graph as new data is collected allowing the “incorporat[ion] of new information without obliterating the results of previous iterations.” Ex1004, 89–90.

153. Olson explains, with respect to maps based on laser scans, that “[o]ur goal is to compute the cost function for a range of rigid-body transformations outputting the rigid-body transformation with the minimum cost.” Ex1004, 119. Olson further explains, 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.

154. Olson depicts that its algorithm solves for a minimum value of the cost function for its map of the Intel Research Center in Figure 4-14, reproduced below.

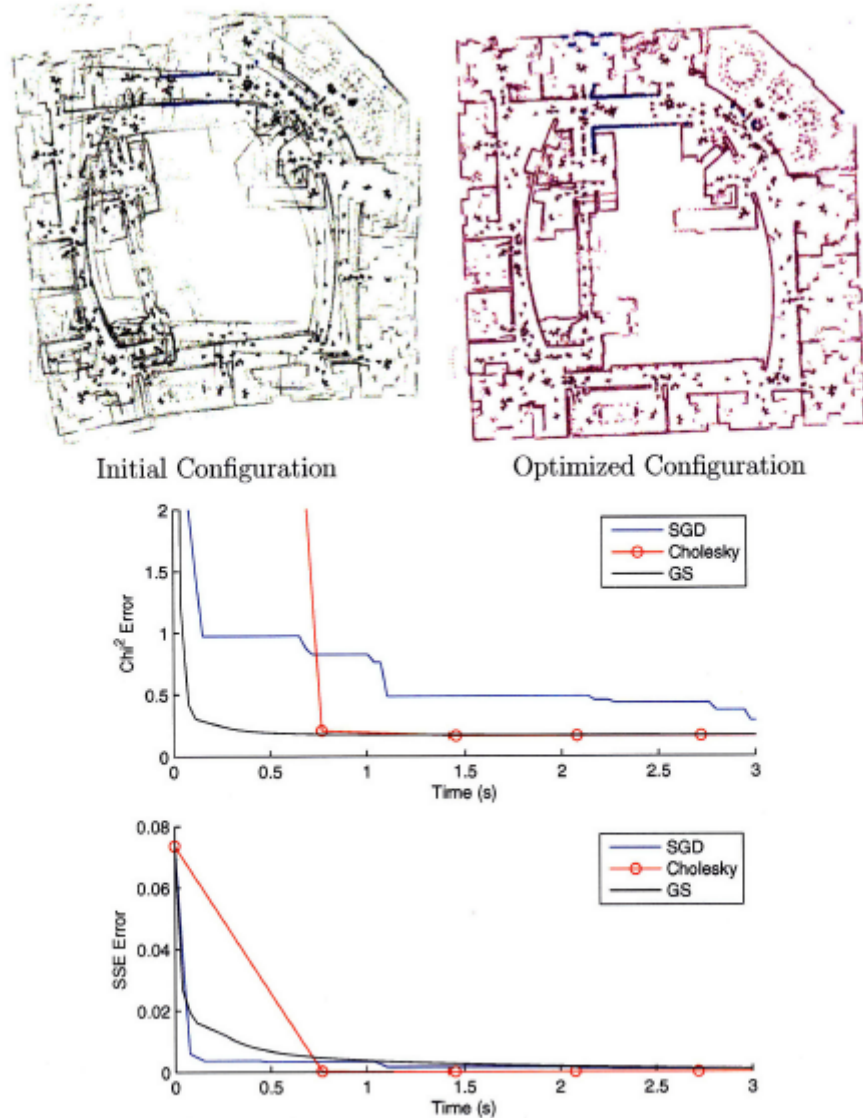


Figure 4-14: Intel Research Center. All the methods achieve very low error, though their convergence rates differ. Note that our method takes a quick and early lead in SSE error, though it lags in χ^2 error.

Ex1004, Fig. 4-14.

155. Olson depicts its hybrid optimization algorithm as iteratively reducing the error until “converged” (finds a minimum value of the cost function) in Algorithm 7, reproduced below.

Algorithm 7 SGD-Optimize-Graph

```
1:  $\lambda = 1/3$ 
2: repeat
3:   Randomly permute order of Constraints
4:   {Update approximation  $M = J^T \Sigma^{-1} J$ . Let  $M_i$  be the  $i^{th}$  diagonal block.}
5:   for all  $\{a, b, t_{ab}, \Sigma_{ab}\}$  in Constraints do
6:     compute  $R$  using Eqn. 4.15
7:      $W = R^T \Sigma_{ab}^{-1} R$ 
8:     for all  $i \in [a + 1, b]$  do
9:        $M_i = M_i + W$ 
10:    Update error-distribution trees with  $M$ 
11:  end for
12: end for
13:  $\Gamma = \max(\Sigma_i^{-1})$ 
14:
15: {Modified Stochastic Gradient Descent}
16: for all  $\{a, b, t_{ab}, \Sigma_{ab}\}$  in Constraints do
17:    $r = X_a^{-1} \oplus X_b$ 
18:    $r(3) = \text{mod2pi}(r(3))$ 
19:   compute  $R$  using Eqn. 4.15
20:    $s = -(b - a)\lambda R^T \Gamma^{-1} \Sigma_{ab}^{-1} r$ 
21:    $s_{max} = X_b - (X_a \oplus T_{ab})$ 
22:    $s = \text{clamp}(s, s_{max})$ 
23:   distribute( $a + 1, b, s$ )
24: end for
25:  $\lambda = \lambda / (\lambda + 1)$ 
26: until converged
```

Ex1004, Algorithm 7.

156. Therefore, it is my opinion that Olson discloses this limitation.

I) 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.

157. In my opinion, Olson discloses this limitation.

158. As explained above with respect to Elements 2[a] and 2[b] (*see supra* Sections VII.A.1.f–g), Olson discloses that each node in its pose/feature graph is a random variable and has an associated probabilistic distribution representing a probability that the respective node is in a respective location (e.g., an uncertainty or confidence ellipse-shaped or circular region surrounding each node). Ex1004, 12–13, 20 (disclosing “[t]he nodes of a pose/feature graph are the same as the random variables of a graphical model.”), 23 (disclosing “confidence is the inverse covariance matrix” Σ^{-1} of a probability distribution), 22 (disclosing “uncertainty [or confidence] can be represented as a probability distribution”), 32 (disclosing that uncertainty or confidence can be measured using “the area of the covariance ellipse, and is thus proportional to the area of the region in which pose [node] *b* is likely to be found given the position of pose [node] *a*.”), 118 (disclosing “range uncertainty” and “probability distributions resemble radially-oriented ellipses ... [and] [i]n practice, [can be] approximate[d] as a circle”); *see also* §§ VII.A.1.f–g.

159. Therefore, it is my opinion that Olson discloses this limitation.

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.

160. In my opinion, Olson discloses this limitation. As explained above with respect to Element 1[d] (*see supra* in Section VII.A.1.e), Olson discloses constraining the start and end locations based on loop closures.

161. Olson further discloses that loop closure involves detection of a home locator. Specifically:

The term “loop closing” arises from the common case where a robot drives in a large loop, returning to its starting point. If, after travelling around the loop, the robot can recognize that it is at its starting position, it “closes” the loop, creating a geometric relationship between the first and last position of the robot. This geometric relationship has two major effects:

- It establishes a *topological* relationship between temporally distant parts of the robot’s trajectory. The robot can use this new topological link as a “short-cut” when planning routes.
- It provides a *metrical* relationship between the beginning and end of the robot’s trajectory that can be used to refine the estimate of the robot’s trajectory, improving upon the estimate provided by dead-reckoning.

...

Loop closing is related to place recognition, which has applications beyond path planning and map building. For example, the same algorithms could be used by a robot to find a recharging station and properly align itself to it.

Ex1004, 13–14.

162. Olson discloses different ways for a robot to detect a home locator. One way is to use “SIFT features extracted from an array of calibrated cameras providing a nearly 360 degree field-of-view.” Ex1004, 34–35. This can be used to determine if the robot has returned to its starting position. Ex1004, 30–31, 34–35. Another way is to use “globally unique beacons such as RFID tags [], wireless networking base stations [], or specialized sensor networks []. The resulting descriptors are

concise and globally unique, but require the deployment of beacons and are not broadly applicable to all robotics applications.” Ex1004, 30.

163. Therefore, it is my opinion that Olson discloses this limitation.

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.

164. In my opinion, Olson discloses this limitation.

165. For example, Olson discloses that map-building is useful for non-autonomous robots and therefore need not be tied to autonomous navigation. Specifically,

Maps are also useful in non-autonomous applications: a human can become disoriented when teleoperating a search-and-rescue robot amidst rubble; a real-time map can make the operators more productive. In these cases, robots use maps in order to complete their missions. The accuracy and quality of the map directly affects their ability to effectively carry out their missions. If an obstacle is poorly localized, a robot may collide with it. If the topological structure of an environment is not properly modeled, a robot may take a needlessly circuitous route to a destination, or fail to find a route entirely.

Ex1004, 9.

166. Therefore, it is my opinion that Olson discloses this limitation.

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;

167. In my opinion, Olson discloses this limitation.

168. As explained with respect to Element 1[c] (*see supra* Section VII.A.1.d), Olson discloses performing scan matching on extended scan groups, the

extended scan groups being determined in-part based on at least two or more nodes of the plurality of nodes.

169. Olson further discloses selecting a root node as a reference location. For example, Olson discloses that the robot collects sensor measurements regarding the robot's position called poses (nodes) and those poses are connected by edges (constraints). Ex1004, 15; *see also* § VII.A.1.e. Specifically, Olson states:

The position of the robot at a particular point in time can be represented as a node in the graph. These types of nodes are known as *poses*. Features (or landmarks) in the environment can also be represented as nodes in the graph: when sensors detect a landmark, the sensor observation is represented as an edge connecting the landmark to the pose from which the observation was made.

Ex1004, 15.

170. As such, each node has a position relative to the initial location. Ex1004, 15, 20–21, Figure 1-4, Figure 2-2. This is demonstrated in Figure 1-4, reproduced below, where each pose is given a position relative to the starting location, pose 0 (a reference location). This is further demonstrated in Figure 2-2, reproduced below, wherein each of poses *a* and *b* are relative (i.e., connected by transforms *A* and *B*, respectively) to the origin, which a POSITA would understand is the root node.

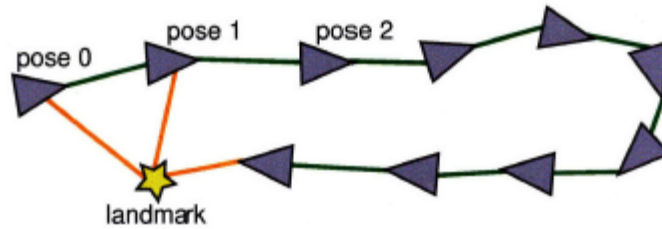


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

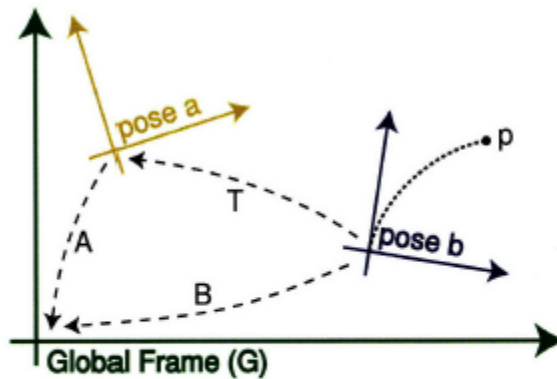


Figure 2-2: Coordinate transformations. Each robot pose represents a local coordinate system which can be related to the global coordinate by a rigid-body transform. Two local coordinate systems can also be related, e.g., $B = AT$. Point p , expressed with respect to coordinate frame B , can be projected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

Ex1004, Figure 2-2.

171. Further, as shown in Figure 1-4, the landmarks (features or obstacles) are represented by feature nodes in the pose/feature graph and these feature nodes are observed by the robot from its pose nodes and given a position relative to the nodes and starting location. Ex1004, 15.

172. Additionally, with respect to the pose nodes at which sensor scans are generated, Olson explains:

[W]e propose a state space representation that approximates the cumulative motion of the robot like x_{rel} , but eliminates the projective effects of the relative representation. We call it “global incremental” state space representation, x_{incr} : the state vector contains the difference between the successive global positions. In absence of rotations ($\theta_i=0$), it is identical to the relative state space. With this state space representation, there are no projective effects (the position of a node is a simple sum of global motions, not the composition of rigid-body transformations), and so updates are more stable.

Ex1004, 63.

173. Olson represents x_{global} , x_{rel} , and x_{incr} as vectors, as depicted in Figure 4-2, reproduced below.

$$\begin{array}{ccc}
 \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ x_1 \\ y_1 \\ \theta_1 \\ x_2 \\ y_2 \\ \theta_2 \\ \dots \end{bmatrix} & \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ \cos(\theta_0)(x_1 - x_0) + \sin(\theta_0)(y_1 - y_0) \\ -\sin(\theta_0)(x_1 - x_0) + \cos(\theta_0)(y_1 - y_0) \\ \theta_1 - \theta_0 \\ \cos(\theta_1)(x_2 - x_1) + \sin(\theta_1)(y_2 - y_1) \\ -\sin(\theta_1)(x_2 - x_1) + \cos(\theta_1)(y_2 - y_1) \\ \theta_2 - \theta_1 \\ \dots \end{bmatrix} & \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \\ x_1 - x_0 \\ y_1 - y_0 \\ \theta_1 - \theta_0 \\ x_2 - x_1 \\ y_2 - y_1 \\ \theta_2 - \theta_1 \\ \dots \end{bmatrix} \\
 \mathbf{x}_{global} & \mathbf{x}_{rel} & \mathbf{x}_{incr}
 \end{array}$$

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; *see also* Ex1004, 61–63. A POSITA would have understood that Olson provides a mathematical relationship between every node, including the initial location (a reference location).

174. As a further example, as discussed with respect to Element 1[c] (*see supra* Section VII.A.1.d), Olson further discloses “[g]iven a pose [node] a [(claimed “selecting a root node as a reference location”)], we wish to find ***all other pose*** [nodes] in the graph whose sensor readings might overlap those from pose [node]

a [(claimed “extended scan groups” including “selecting root node (e.g., pose node *a*) as a reference location)]]” Ex1004, 32.

175. Additionally, Olson discloses, with respect to scan matching for camera images, “[w]henver a camera frame arrives, a new set of SIFT features are extracted. These features are matched against a set of “tracks”: each track maintains *a “reference”* SIFT descriptor [(corresponding to a selected pose node for that track as a reference location)] and a list of observations matching that descriptor. Each observation includes both a vehicle position and the bearing to the SIFT feature.” Ex1004, 110.

176. Therefore, it is my opinion that Olson discloses this limitation.

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 node [sic] is different from the respective node; and

177. In my opinion, Olson discloses this limitation.

178. As discussed with respect to Elements 1[c] (*see supra* Section VII.A.1.d), Olson discloses using scan matching (finding overlap in measurements of distinct features taken at two of the respective nodes of the plurality of nodes), which estimates a rigid body transform by aligning corresponding features found in pairs of scans. Ex1004, 31, 34, 117, 119–22. It does so, for example, by computing a pair-wise consistency matrix to determine which hypothesized matches are most self-consistent. Ex1004, 37–40.

179. As a further example, Olson discloses calculation of a rigid-body transform, T , between poses a and b, where the root node is the origin, based on scan matching (at least two nodes that are not the root node). Ex1004, 20–21. Olson depicts this in Figure 2-2, reproduced below.

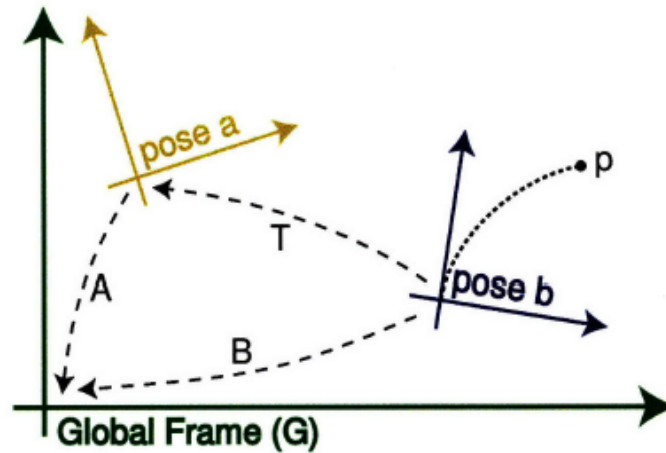


Figure 2-2: Coordinate transformations. Each robot pose represents a local coordinate system which can be related to the global coordinate by a rigid-body transform. Two local coordinate systems can also be related, e.g., $B = AT$. Point p , expressed with respect to coordinate frame B , can be projected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

Ex1004, Figure 2-2.

180. Olson further discloses that “[t]he first step in identifying loop closure hypotheses is to identify those poses that might contain *overlapping sensor readings*,” the overlap being determined via scan matching. Ex1004, 32. 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* ”. Ex1004, 32. A POSITA would have understood that reference to all nodes with overlapping

sensor readings discloses the claimed “at least two of the respective nodes of the plurality of nodes, the root node [sic] is different than the respective node.”

181. Therefore, it is my opinion that Olson discloses this limitation.

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.**

182. In my opinion, Olson discloses this limitation.

183. As discussed above with respect to Elements 1[c] (*see supra* Section VII.A.1.d), Olson discloses extended scan groups based on scan matching, which in turn uses overlapping distinct features of the scans (each scan being generated at the at least two of the respective pose nodes) to estimate a rigid-body transform for aligning the scans. Ex1004, 116–17, 119–20, Figure A-9.

184. Olson further discloses grouping the at least two of the respective nodes into extended scan groups based on overlapping distinct features of the scans at the at least two of the respective nodes. For example, Olson 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. 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.

185. Therefore, it is my opinion that Olson discloses this limitation.

r) Element 8[pre]: A robot, comprising:

186. To the extent the preamble is limiting, it is my opinion that Olson discloses it.

187. Olson discusses examples of robots, explains several robotic functions, and explains that its algorithm is designed to be integrated with robots to enable mapping, localization, and navigation functions. Ex1004, 9–16; *see also* §§ VII.A.1.a–c. Olson further depicts several robots which either use or would advantageously use its algorithms in Figures 1-1 and 6-1, reproduced below.

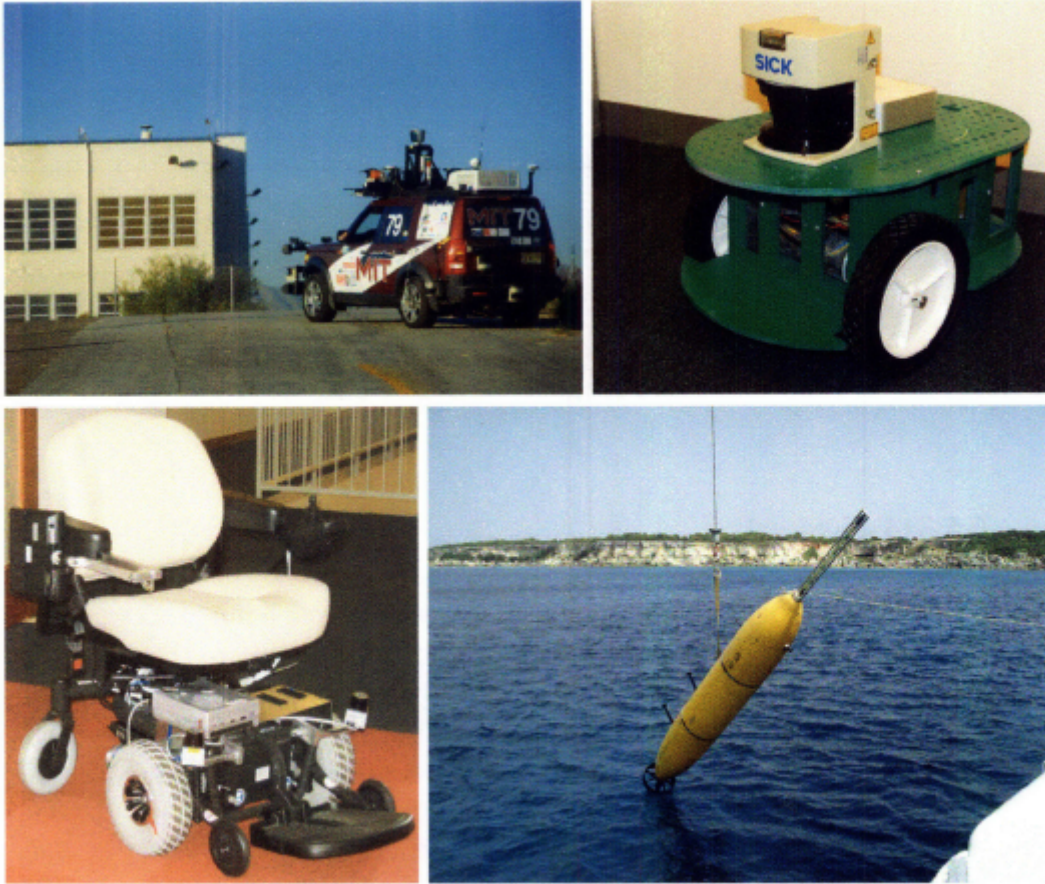


Figure 1-1: Robot Applications. Map building arises in many contexts, including autonomous cars [37], indoor surveying [68], underwater robots for ship-hull inspection [75], and human-centric assistive robotics [57].

Ex1004, Figure 1-1.



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

Ex1004, Figure 6-1.

188. Therefore, it is my opinion that Olson discloses this limitation.

- 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**

189. In my opinion, Olson discloses this limitation.

190. This limitation was addressed in the discussion of Element 1[b], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.c.

- t) **Element 8[b]: a mapping and localization unit configured to execute computer readable instructions to:**

191. In my opinion, Olson discloses this limitation.

192. As discussed above with respect to Element 8[pre] (*see supra* Section VII.A.1.r), Olson discloses its algorithm is designed to work with robots to enable mapping, localization, and navigation functions. Ex1004, 9–16; *see also* Ex1004, 55 (explaining that stochastic gradient descent methods may be used for robot localization); Ex1004, 34–35, 110–113 (explaining that the system localizes landmarks); §§ VII.A.1.a–c (disclosing mapping and navigation functions).

193. Olson further discloses the robot’s memory and the impact the disclosed algorithm has on the memory, including storage space and bandwidth. Ex1004, 30. Specifically, Olson states “[t]he length of these feature vectors has a major impact on both total memory usage and the time required to index and search for similar features.” Ex1004, 30. Further, Olson states that its “method also has low memory requirements and is relatively easy to implement.” Ex1004, 55.

194. In addition, Olson discusses “memory usage of the algorithm,” “runtime” and “CPU requirements.” Ex1004, 98. A POSITA would have understood that disclosure of a robot memory with memory that performs mapping and localization functions also discloses a mapping and localization unit, because otherwise it would not be able to perform the algorithms disclosed in Olson. Ex1004, 98.

195. Therefore, it is my opinion that Olson discloses this limitation.

- u) **Element 8[b][1]: generate a graph of the plurality of nodes based at least in part on the generated scans;**

196. In my opinion, Olson discloses this limitation.

197. This limitation was addressed in the discussion of Element 1[b], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.c.

- v) **Element 8[b][2]: determine extended scan groups in-part on at least two or more nodes of the plurality of nodes;**

198. In my opinion, Olson discloses this limitation.

199. This limitation was addressed in the discussion of Element 1[c], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.d.

- w) **Element 8[b][3]: perform scan matching on the extended scan groups; and**

200. In my opinion, Olson discloses this limitation.

201. This limitation was addressed in the discussion of Element 1[c], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.d.

- 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.**

202. In my opinion, Olson discloses this limitation.

203. This limitation was addressed in the discussion of Element 1[d], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.e.

- 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.

204. In my opinion, Olson discloses this limitation.

205. This limitation was addressed in the discussion of Element 2[b], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.g.

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.

206. In my opinion, Olson discloses this limitation.

207. This limitation was addressed in the discussion of Claim 3, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.j–k.

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.

208. In my opinion, Olson discloses this limitation.

209. This limitation was addressed in the discussion of Element 2[d], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.i.

**bb) Claim 12: The robot of claim 8, further comprising:
an actuator configured to move the robot between
locations in the environment.**

210. In my opinion, Olson discloses this limitation.

211. This limitation was addressed in the discussion of Element 1[a], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.b. A POSITA would have understood that an actuator configured to move the robot is nothing more than a mechanical means for moving the robot. For example, the '325 Patent explains,

In some implementations, actuator units 268 can include actuators such as electric motors, gas motors, driven magnet systems, solenoid/ratchet systems, piezoelectric systems (e.g., inchworm motors), magnetostrictive elements, gesticulation, and/or any way of driving an actuator known in the art. By way of illustration, such actuators can actuate wheels or other displacement enabling drivers (e.g., mechanical legs, jet engines, propellers, hydraulics, etc.). For example, actuator units 268 can allow robot 202 to move and/or navigate through environment 200 and/or any other environment.

Ex1001, 10:45–55. *See also* Ex1001, 8:44–48 (describing an “actuator unit”), FIG.

3.

212. It is therefore my opinion that the claimed actuator is disclosed in Olson by the disclosure of wheels, motors, and other means for moving a robot as described in Section VII.A.1.b.

**cc) Claim 13: The robot of claim 8, further comprising: a
user interface for controlling the robot by at least one
user.**

213. In my opinion, Olson discloses this limitation.

214. As explained above with respect to Claim 6 (*see supra* Section VII.A.1.n), Olson discloses that a robot with mapping functionalities may be advantageously under the control of a user, *e.g.*, user controlling the robot's navigation during a search-and-rescue operation. Ex1004, 9. A POSITA would have understood that disclosure of a robot operating under the navigational control of a user also discloses a means for the user to exercise that control, *i.e.*, a user interface.

215. Therefore, it is my opinion that Olson discloses this limitation.

dd) Claim 14: The robot of claim 8, further comprising: a navigation unit configured to navigate the robot autonomously without the user.

216. In my opinion, Olson discloses this limitation.

217. As discussed above with respect to Elements 8[pre] and 8[b] (*see supra* Section VII.A.1.r, t), Olson discloses its algorithm is designed to work with robots to enable mapping, localization, and navigation functions. Ex1004, 9–16, 34–35, 55, 109-122; *see also* §§ VII.A.1.a–c. Olson further discloses “memory usage of the algorithm,” “runtime” and “CPU requirements.” Ex1004, 30, 98. A POSITA would have understood that disclosure of a robot memory with memory that performs navigation functions also discloses a navigation unit, because otherwise it would not be able to perform the algorithms disclosed in Olson. Ex1004, 98.

218. Olson further discloses that the robot may be configured to navigate autonomously without the user.

219. For example, Olson discloses that its mapping algorithm is intended to further enable autonomous navigation. Ex1004, 9 (“Consequently, map building is a critical component of almost every autonomous robot.”). Olson further depicts several robots which navigate autonomously in Figure 1-1, reproduced below.

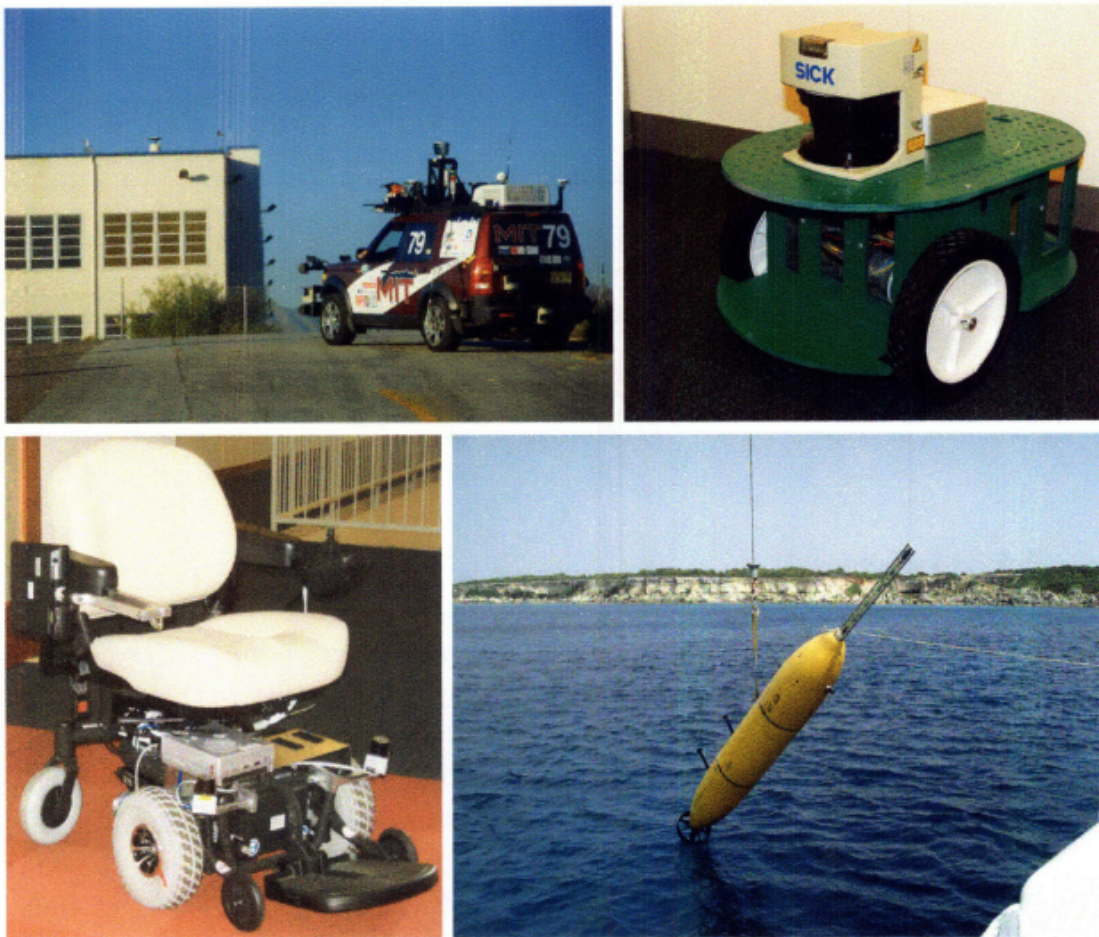


Figure 1-1: Robot Applications. Map building arises in many contexts, including autonomous cars [37], indoor surveying [68], underwater robots for ship-hull inspection [75], and human-centric assistive robotics [57].

Ex1004, Figure 1-1.

220. Olson further discloses that it produced one of its data sets with a robot that mapped an obstacle course while navigating through the course autonomously. Ex1004, 44, 109–10. Olson depicts the robot (a modified car) in Figure A-1, reproduced 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.

221. Therefore, it is my opinion that Olson discloses this limitation.

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:

222. To the extent the preamble is limiting, it is my opinion that Olson discloses it.

223. Olson discusses the robot's memory and the impact its disclosed system has on the memory, including storage space and bandwidth. Ex1004, 30.

Specifically, Olson states “[t]he length of these feature vectors has a major impact on both total memory usage and the time required to index and search for similar features.” Ex1004, 30. Further, Olson states that its “method also has low memory requirements and is relatively easy to implement.” Ex1004, 55.

224. In addition, Olson discusses “memory usage of the algorithm,” “runtime” and “CPU requirements.” Ex1004, 98. A POSITA would have understood that disclosure of a robot memory with memory that performs certain functions also discloses computer readable instructions stored therein, because otherwise it would not be able to perform the algorithms discussed in Olson. Ex1004, 98.

225. Therefore, it is my opinion that Olson discloses this limitation.

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;

226. In my opinion, Olson discloses this limitation.

227. As explained above with respect to Element 1[b] (*see supra* Section VII.A.1.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.

228. Further, as explained above with respect to Elements 8[b] and 15[pre] (*see supra* Sections VII.A.1.t, ee), the robot comprises a memory and processor that

provide a means for the robot to map and navigate an environment using these sensors. A POSITA would have understood that these memory and processors control the manner in which scans are generated in association with the location in the environment by transmitting a signal to the at least one sensor to generate scans of the environment.

229. Therefore, it is my opinion that Olson discloses this limitation.

gg) Element 15[b]: generate a graph of the plurality of nodes based in-part on the generated scans;

230. In my opinion, Olson discloses this limitation.

231. This limitation was addressed in the discussion of Elements 1[b] and 8[b][1], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.c, u.

hh) Element 15[c]: determine extended scan groups based at least in part on two or more nodes of the plurality of nodes;

232. In my opinion, Olson discloses this limitation.

233. This limitation was addressed in the discussion of Elements 1[c] and 8[b][2], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.d, v.

ii) Element 15[d]: perform scan matching on the extended scan groups; and

234. In my opinion, Olson discloses this limitation.

235. This limitation was addressed in the discussion of Elements 1[c] and 8[b][3], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.d, w.

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.

236. In my opinion, Olson discloses this limitation.

237. This limitation was addressed in the discussion of Elements 1[d] and 8[b][4], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.e, x.

kk) Claim 16: The non-transitory computer-readable medium of claim 15, wherein each extended scan group includes at least three or more scans.

238. In my opinion, Olson discloses this limitation.

239. As explained above with respect to Element 1[c] and Claim 7 (*see supra* Sections VII.A.1.d, o–q), Olson discloses that “[t]he first step in identifying loop closure hypotheses is to identify those poses that might contain overlapping sensor readings,” the overlap being determined via scan matching. Ex1004, 32. 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. A POSITA would have understood that reference to ***all*** nodes with

overlapping sensor readings discloses the claimed “each extended scan group includes at least three or more scans.”

240. Therefore, it is my opinion that Olson discloses this limitation.

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.

241. In my opinion, Olson discloses this limitation.

242. This limitation was addressed in the discussion of Element 3[a] and Claim 10, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.j, z.

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.

243. In my opinion, Olson discloses this limitation.

244. This limitation was addressed in the discussion of Element 3[b] and Claim 10, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.k, z.

B. Ground 2: Claims 1–18 are Anticipated by Stachniss

245. In my opinion, claims 1–18 of the '325 patent are anticipated by Stachniss.

1. Element-by-Element Analysis

a) Element 1[pre]: A method of generating a map by a robot, comprising:

246. To the extent the preamble is limiting, it is my opinion that Stachniss discloses it.

247. For example, Stachniss discloses a method of generating a map by a robot as it traverses the environment, within a class of methods called “Simultaneous Localization and Mapping” (SLAM) methods. Ex1005, 1153. Stachniss further explains that SLAM is “one of the key enabling technologies of robot navigation.” Ex1005, 1153–54.

248. Stachniss explains that, as the robot moves, the robot records, at each of its locations x_t , through its sensor(s), a sequence of measurements z_t of objects (or features) in the environment and these measurements z_t are stored in a set Z_T . Ex1005, 1154, 1160, 1162–66, Fig. 46.1, Fig. 46.3, Fig. 46.7a–c. Stachniss further explains that the robot collects this information as it travels through an environment and simultaneously uses the information to create the “best estimate for the map” of the environment. Ex1005, 1163.

249. Stachniss further discloses that a robot can create a map of an environment and a route on the map based on sensor measurements. Ex1005, 1154, 1160, 1162–66. Stachniss explains that, as the robot moves, the robot records, at each of its locations x_t , through its sensor(s), a sequence of measurements z_t of objects (or features) in the environment and these measurements z_t are stored in a set Z_T . Ex1005, 1154, 1160, 1162–66, Fig. 46.1, Fig. 46.3, Fig. 46.7a–c. Stachniss further explains that the robot collects this information as it travels through an environment and simultaneously uses the information to create the “best estimate for the map” of the environment. Ex1005, 1163. For example:

Landmarks 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 . Further edges exist between the nodes that correspond to locations x_t and landmarks m_i , assuming that at time t the robot sensed landmark i . Edges in this graph are soft constraints. Relaxing these constraints yields the robot’s best estimate for the map and the full path.

Ex1005, 1162–63.

250. The result is depicted in Fig. 46.7a–c, reproduced below.

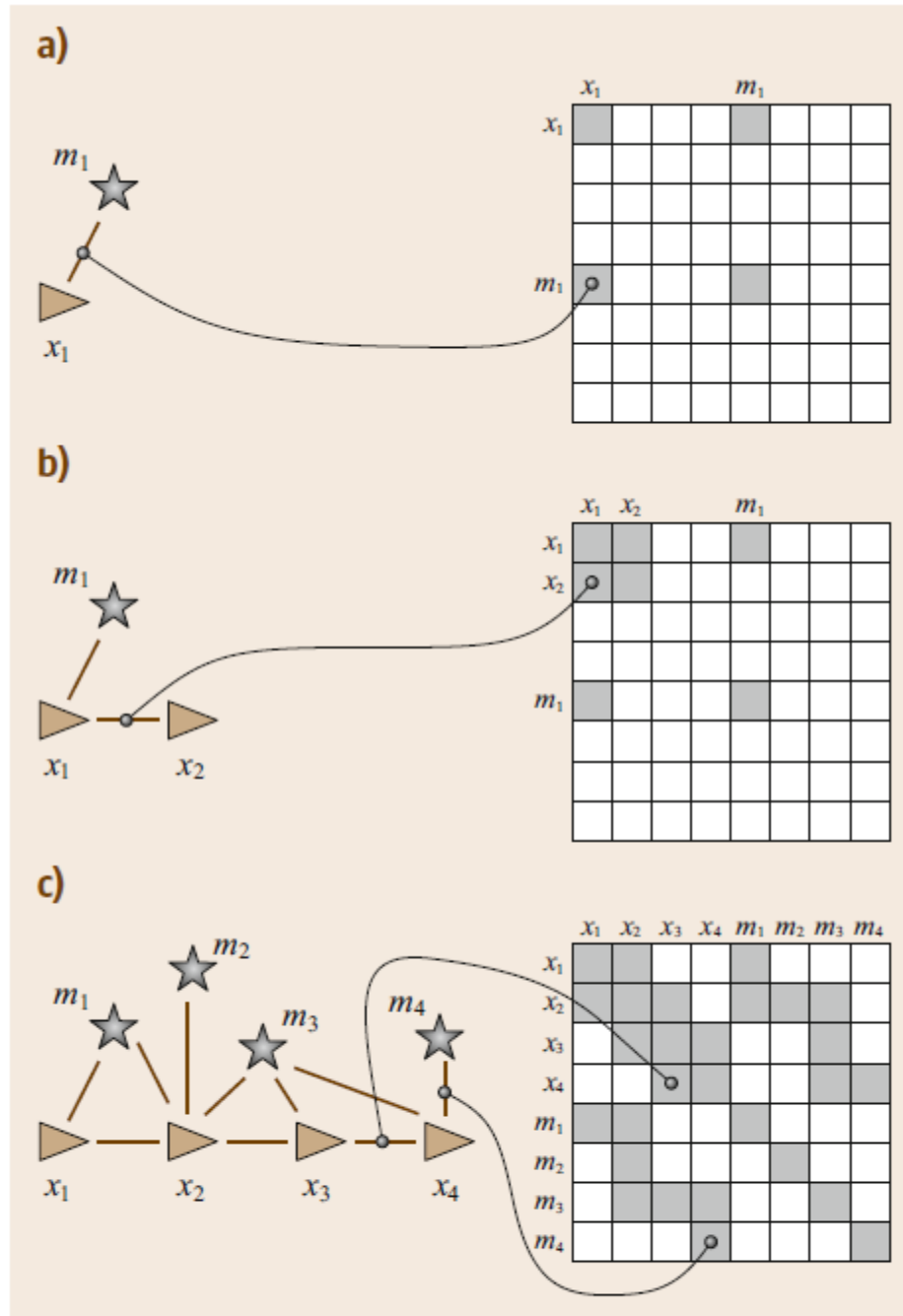


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a-c.

251. Figure 46.11 (reproduced below) in Stachniss is an example of a map generated in real-time.

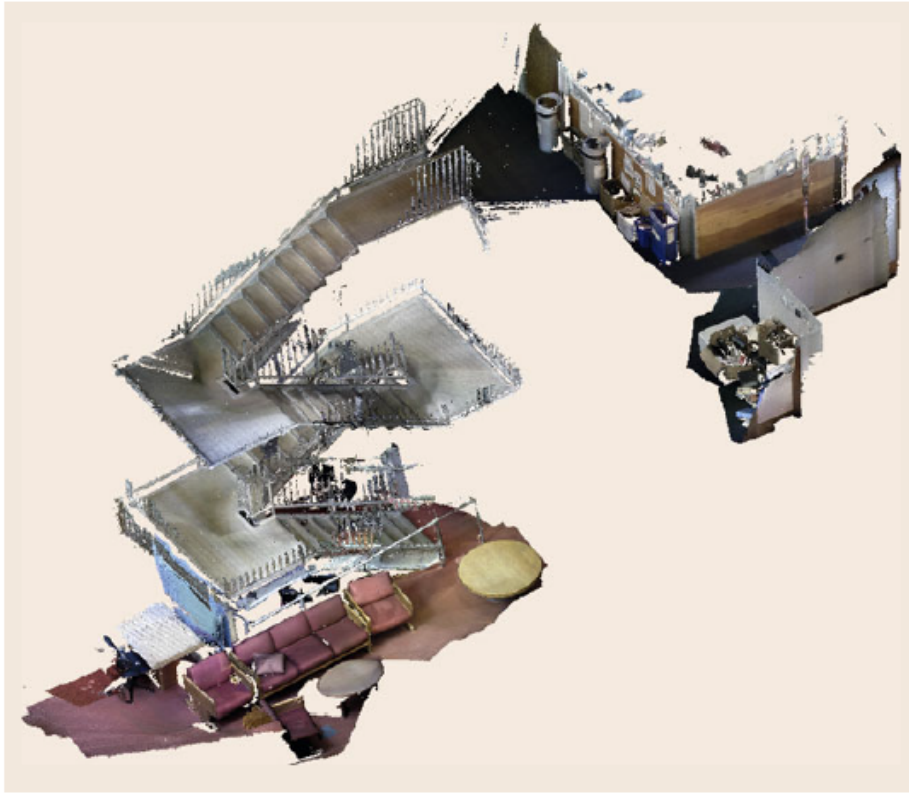


Fig. 46.11 Spatially extended KinectFusion output produced in real-time with Kintinuous (after [46.139])

Ex1005, Fig. 46.11.

252. Therefore, it is my opinion that Stachniss discloses this limitation.

b) Element 1[a]: traveling, by the robot, in an environment;

253. It is my opinion that Stachniss discloses this limitation.

254. Stachniss discloses a method that allows a robot to simultaneously map an environment as it travels through that environment. Ex1005, 1153–1154. Specifically, Stachniss attempts to solve what it calls the SLAM problem. Ex1005, 1154. SLAM stands for simultaneous localization and mapping. Ex1005, 1153.

The SLAM problem is defined as follows: A mobile robot roams an unknown environment, starting at an initial location x_0 . Its motion is uncertain, making it gradually more difficult to determine its current pose in global coordinates. As it roams, the robot can sense its environment with a noisy sensor. The SLAM problem is a problem of building a map of the environment while simultaneously determining the robot's position relative to this map given noisy data.

Ex1005, 1154.

255. Stachniss discloses a system that solves the SLAM problem.

[Stachniss] reviews three basic SLAM paradigms, from which most others are derived. The first, known as EKF SLAM, is in robotics historically the earliest but has become less popular due to its limiting computational properties and issues resulting from performing single linearizations only. The second approach uses nonparametric statistical filtering techniques known as particle filters. It is a popular method for online SLAM and provides a perspective on addressing the data association problem in SLAM. The third paradigm is based on graphical representations and successfully applies sparse nonlinear optimization methods to the SLAM problem. It is the main paradigm for solving the full SLAM problem and recently also incremental techniques are available.

Ex1005, 1157.

256. These paradigms “address[] the problem of acquiring a spatial map of an environment while simultaneously localizing the robot relative to this model.”

Ex1005, 1153.

257. Stachniss discloses robots that store the sequence of the robot's locations (path traveled by the robot) in a set, X_T , consisting of a sequence of three-dimensional vectors $x_0, x_1, x_2, \dots, x_T$, wherein a three-dimensional vector x_t corresponds to the location (e.g., 2D position and orientation for a robot traveling on

a flat ground) of the robot at time t . Stachniss further explains that the relative motion of the robot between two consecutive locations along the path is characterized by a sequence of odometry measurements $u_1, u_2, \dots, u_T$, stored in a set U_T , wherein u_t characterizes the relative motion of the robot between time $t-1$ and t . Stachniss further explains that, as the robot moves, the robot records, at each of its locations x_t , through its sensor(s), a sequence of measurements z_t of objects (or features) in the environment and these measurements z_t are stored in a set Z_T . Ex1005, 1154, 1160, 1162–66, Fig. 46.1, Fig. 46.3, Fig. 46.7a–c. Stachniss further explains that the robot collects this information as it travels through an environment and simultaneously uses the information to create the “best estimate for the map” of the environment. Ex1005, 1163. The robot uses the estimated map to travel along a route. Ex1005, 1153–1154. For example, Stachniss explains that maps developed in real-time allow robots to autonomously navigate (*i.e.*, travel) to un- or under-explored areas in order to improve the map. Ex1004, 1164 (“[I]ncremental optimization techniques have been proposed that aim at providing a sufficient but not necessarily perfect model of the environment at every point in time. This allows a robot to make decisions based on the current model, for example, to *determine exploration goals*.”).

258. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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;

259. It is my opinion that Stachniss discloses this limitation.

260. Stachniss discloses that its method generates a graph comprising a plurality of nodes. For example, Stachniss discloses that a robot can create a map of an environment and a route on the map based on generating a graph wherein each node is associated with a scan generated by a sensor of the robot at a location in the environment. Ex1004, 1162–66. Specifically, Stachniss states,

Landmarks 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 . Further edges exist between the nodes that correspond to locations x_t and landmarks m_i , assuming that at time t the robot sensed landmark i . Edges in this graph are soft constraints. Relaxing these constraints yields the robot's best estimate for the map and the full path.

Ex1005, 1162–63.

261. The result is depicted in Fig. 46.7a–c, reproduced below.

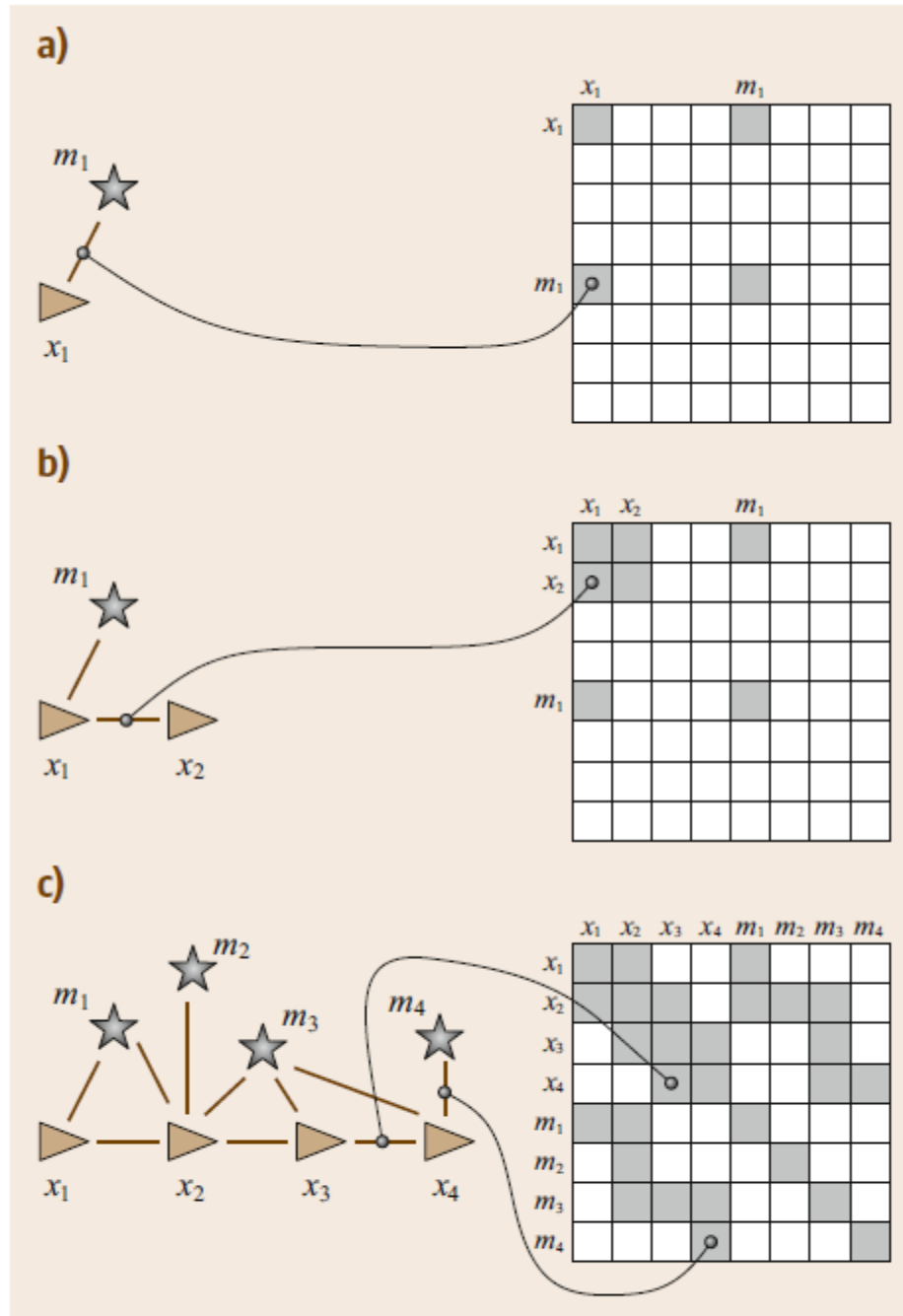


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a-c.

262. Stachniss further discloses that, in its method, 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. For example, Stachniss discloses that the robot uses sensors to gather information regarding the environment as it travels along a route. Specifically, Stachniss states that a “[a]s it roams, the robot can sense its environment with a noisy sensor.” Ex1005, 1154. Stachniss discloses that the sensors can be sensors in the wheels or motors, positioning system, laser scanners, and cameras. Ex1005, Abstract, 1153, 1164, 1166–69. Odometry measurements are taken by the robot as it travels along a route in order to gather information between two locations. Ex1005, 1154; *see also* Ex1005, Abstract, 1153, 1164, 1166–69. The gathered information results in the ability to “recover[] a model of the world [(environment)’s true map] m and the sequence of robot locations X_T from the odometry [U_T] and [other sensor (e.g., camera)] measurement [Z_T] data.” Ex1005, 1155; *see also* Ex1005, 1154. Fig. 46.1, reproduced below, illustrates a graphical model of the SLAM problem with the environment represented by its true map m (that is being estimated by SLAM) and with the involved variables representing the robot’s locations x_t (that are being estimated by SLAM), the robot’s odometry measurements u_t , and the robot’s sensor measurements z_t .

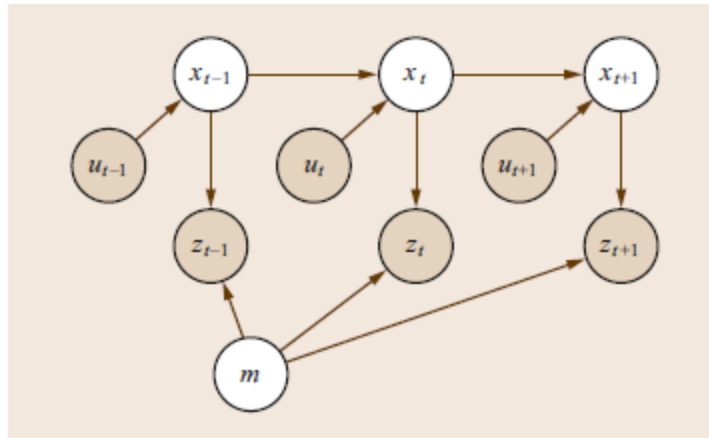


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

263. Therefore, it is my opinion that Stachniss discloses this limitation.

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

264. It is my opinion that Stachniss discloses this limitation.

265. Stachniss further explains that a robot may use “visual odometry” (scan matching) to estimate the distance traveled along the route. Ex1005, 1168. For example, Stachniss further explains:

As pointed out by Davison and other researchers, an appealing aspect of visual SLAM is that camera measurements can provide odometry information, and indeed visual odometry is a key component of modern SLAM systems [46.127]. Here, [46.128] and [46.129] provide an extensive tutorial of techniques for visual odometry, including feature detection, feature matching, outlier rejection, and constraint estimation, and trajectory optimization. Finally, a publicly available visual odometry library [46.130] that is optimized for efficient operation on small unmanned aerial vehicles is available today.

Ex1005, 1168.

266. In the above, Stachniss refers to a two-part paper by Scaramuzza and Fraundorfer on “Visual Odometry” that discusses feature detection and matching, outlier rejection, and other machine vision techniques that were well-known in the art. Ex1005, 1168, 1174. Feature detection refers to algorithms, like SIFT and SURF, which identify unique patterns in visual scans of an environment which might be identified in other scans of the same environment, for example from different positions. Feature matching refers to algorithms in which feature descriptors, such as SIFT or SURF feature descriptors, are used to match (e.g., measure similarity between) detected features in two or more scans (e.g., two or more images taken from different positions) in order to determine any overlap between the two or more scans for the purpose of scan matching and alignment. Robust feature matching with outlier rejection refers to algorithms like RANSAC which can identify and remove false matches after SIFT/SURF descriptors are used to match SIFT/SURF-identified features in two or more scans (images). By identifying the same features in multiple images at different locations, algorithms may calculate a robot movement that would result in the relative movement of various features. In Table 46.1, a table listing “Recent open-source graph-based SLAM implementations,” Stachniss identifies a paper (reference [46.86] in Stachniss) as “RGBD-SLAM,” and describes its approach as a “[*f*airly *s*tandard combination of SURF matching and RANSAC.”

Ex1005, 1165. Stachniss therefore discloses this element and explains that it was “fairly standard” prior to the priority date of the challenged patent.

267. Stachniss further discloses that nodes may be grouped according to detection of the same landmark, which corresponds to “extended scan groups being determined in-part on at least two or more nodes of the plurality of nodes.” Ex1005, 1163. For example, as depicted in Fig. 46.7a–c, reproduced below, Stachniss represents the graph as a sparse matrix of edges between poses and between poses and landmarks, and the robot senses the same landmark from the same pose. Ex1005, 1165. Stachniss further explains that the graph is optimized to find the maximum-likelihood graph according to the information provided by all edges. Ex1005, 1162–66. A POSITA would have understood that edges connecting each of a set of nodes to the same landmark will constrain the optimization with respect to those nodes such that they are optimized together, therefore disclosing an extended scan group.

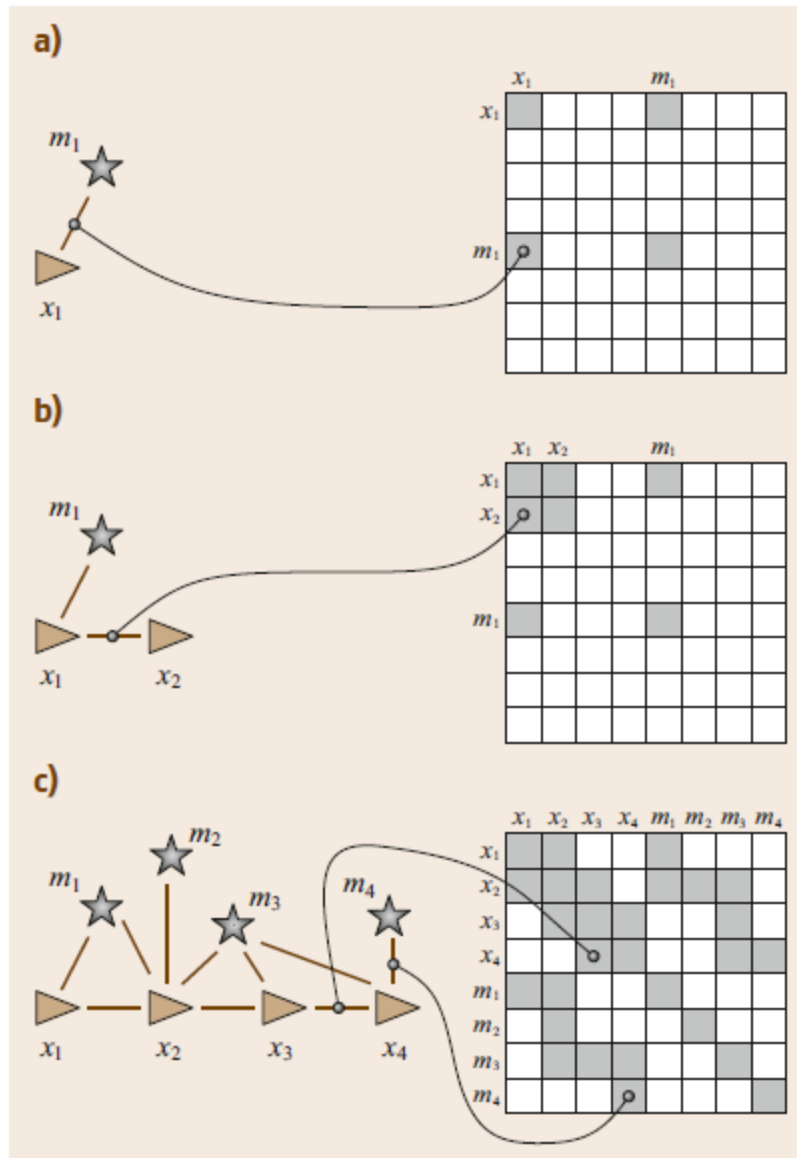


Fig.46.7a–c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation is landmark m_1 . (b) Robot motion from x_1 to x_2 . (c) Several steps later

Ex1005, Fig. 46.7.

268. Stachniss further discloses that some graph-based SLAM methods, such as “Hierarchical SLAM,” formally assign nodes to groups (extended scan groups) for optimization within the group. Ex1005, 1163–64. Stachniss explains

that this approach may be useful for building a large map in real-time by avoiding simultaneous optimization of the entire graph each time a new node is added.

Ex1005, 1164. For example, Stachniss explains,

Extensions to support an effective correction of large-scale graphs are hierarchical methods. One of the first is the ATLAS framework [46.25], which constructs a two-level hierarchy combining a Kalman filter that operates in the lower level and a global optimization at the higher level. Similar to that, Hierarchical SLAM [46.68] is a technique for using *independent local maps* (extended scan groups), which are merged in case of re-visiting a place. A fully hierarchical approach has been presented in [46.65]. It builds a multilevel pose-graph and 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. An alternative hierarchical approach is [46.69], which recursively partitions the graph into multiple-level submaps using the nested dissection algorithm.

Ex1005, 1163–64.

269. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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.**

270. It is my opinion that Stachniss discloses this limitation.

271. For example, Stachniss discloses loop closing based on the detection of features in the environment. Ex1005, 1157–59. “The ability to close loops is a key characteristic of modern-day SLAM algorithms” because of the helpful effect of loop closing on reducing the uncertainty in the mapping and localization. Ex1005, 1156. Further, loop closing is possible when the robot “reach[es] the *same location*

[the start location and end location being at a substantially similar location in the environment] from multiple directions.” Ex1005, 1156. Stachniss explains that a robot starts at an initial location (start location), x_0 , which position may be known precisely. Ex1005, 1154, 1157–59. At x_0 , as at every node, the robot may “sense[] objects in the environment.” Ex1005, 1154. When the robot encounters those objects again later in its route, it can associate later measurements with earlier measurements and thereby determine that it has returned to its initial position. Ex1005, 1158, 1161. Stachniss further explains that loop closing may be enhanced by visual sensors, which can use “appearance information” to detect features in the environment associated with the start location. Ex1005, 1166, 1168.

272. Stachniss discloses that loop closures reduce the uncertainty of the map by determining that the robot has “reach[ed] the same location.” Ex1005, 1156–58. Stachniss further discloses that the algorithm may additionally impose an absolute ***constraint*** by eliminating the end pose entirely, and then connecting all nodes previously connected to the end node to the start node. Ex1005, 1164. Loop closure reduces the uncertainty of the graph (e.g., uncertainty in the locations of nodes) by providing additional information to the optimization function. Ex1005, 1162–64.

273. Stachniss depicts the uncertainty-reducing effect of loop closure in Figure 46.2 (reproduced below). Ex1005, 1157–58. As the robot travels, uncertainty accrues, increasing the range of possible locations associated with the

robot, as shown in Figure 46.2.a–d (reproduced below). But when “the robot observes [again at the end node] the [first] landmark it saw [at its start node] in the very beginning of the mapping,” it *imposes a constraint between the start and end nodes*, “and the uncertainty of all landmarks decreases, as does the uncertainty of its current pose.” Ex1005, 1158.

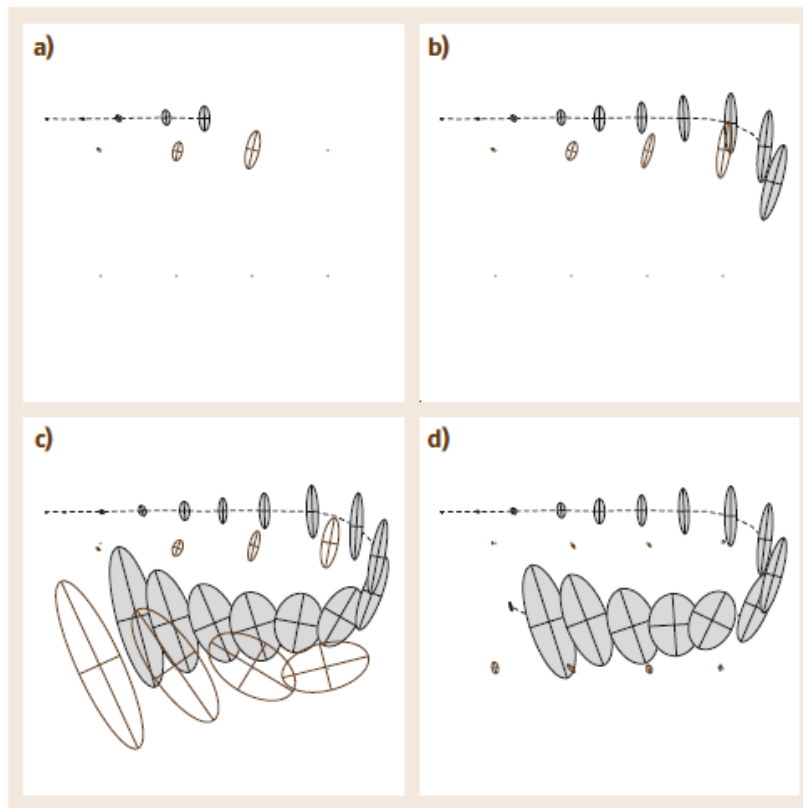


Fig.46.2a–d EKF applied to the online SLAM problem. The robot’s path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the 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. 46.2a–d.

274. Therefore, it is my opinion that Stachniss discloses this limitation.

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;

275. It is my opinion that Stachniss discloses this limitation.

276. Stachniss explains that SLAM methods estimate position based on measures of movement, like odometry, and sensor measurements of landmarks (scan matching) by the robot at each of its positions. Ex1005, 1155. These estimates are the most-probable locations given all the data available to the robot. Ex1005, 1155. As Stachniss explains, these most-probable locations are best thought of as the peak of a probabilistic distribution associated with each node, which corresponds to the mean or center for a Gaussian probabilistic distribution. Ex1005, 1155. Stachniss further discloses:

In SLAM, it is common to think of those mathematical models as probability distributions: $p(x_t | x_{t-1}, u_t)$ characterizes the probability distribution of the location x_t assuming that a robot started at a known location x_{t-1} and measured the odometry data u_t . And likewise, $p(z_t | x_t, m)$ is the probability for measuring z_t if this measurement is taken at a known location x_t in a known environment m . Of course, in the SLAM problem we do *not* know the robot location, and neither do we know the environment. As we shall see, Bayes rule takes care of this, by transforming these mathematical relationships into a form where we can recover probability distributions over those latent variables from the measured data.

Ex1005, 1155.

277. Stachniss further discloses that the probabilistic function of the full SLAM problem can be expressed in terms of the nodes' probabilistic distributions, wherein a probability distribution at each pose node in the graph corresponds to a surrounding region (range) around its corresponding pose node, wherein the surrounding region represents the possible locations (range) of the true positions of the robot. Ex1005, 1155, 1157–58, 1163, Fig. 46.2a–d (showing surrounding region

around each node as ellipse), Equations (46.16)-(46.18). Stachniss explains that “in the SLAM problem we do not know the robot location. . . . Bayes rule takes care of this, by transforming these mathematical relationships into a form where we can recover probability distributions over those latent variables [(e.g., robot’s positions x_t)] from the measured data.” Ex1005, 1155.

278. Stachniss further explains with respect to graph-based SLAM that “the graph corresponds to the log-posterior [probabilistic distribution] of the full SLAM problem” and that the solution is the one that maximizes the log-posterior probabilistic distribution. Ex1005, 1163; Equation 46.17. Stachniss further discloses an equation that corresponds to the log of the posterior probability distribution (reproduced below) that incorporates uncertainty (a range of possible locations in the environment associated with the respective one of the plurality of nodes), in the sensed environment feature data (e.g., using scan-matching), also denoted as feature observation data. Ex1005, 1163.

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

In the equation above, the uncertainty is represented in terms of the covariance matrices (R_t for the odometry reading and Q_t for the sensed environment features).

Ex1005, 1157 (disclosing “error covariance matrix representing the uncertainty in the[] estimates”).

279. Stachniss also discusses that each node has an uncertainty range for both poses (nodes corresponding to robot’s locations at which measurements are taken by at least one sensor, e.g., odometry sensor and/or vision sensor) and landmarks (environment features observed by robot from robot’s locations (i.e, from the pose nodes)) as illustrated in Figure 46.2 (reproduced below). *See also* Ex1005, 1157–58 (disclosing in reference to Fig. 46.2 that “[a]s [robot] moves, its own pose uncertainty increases, as indicated by uncertainty ellipses of growing diameter”), 1155, 1163.

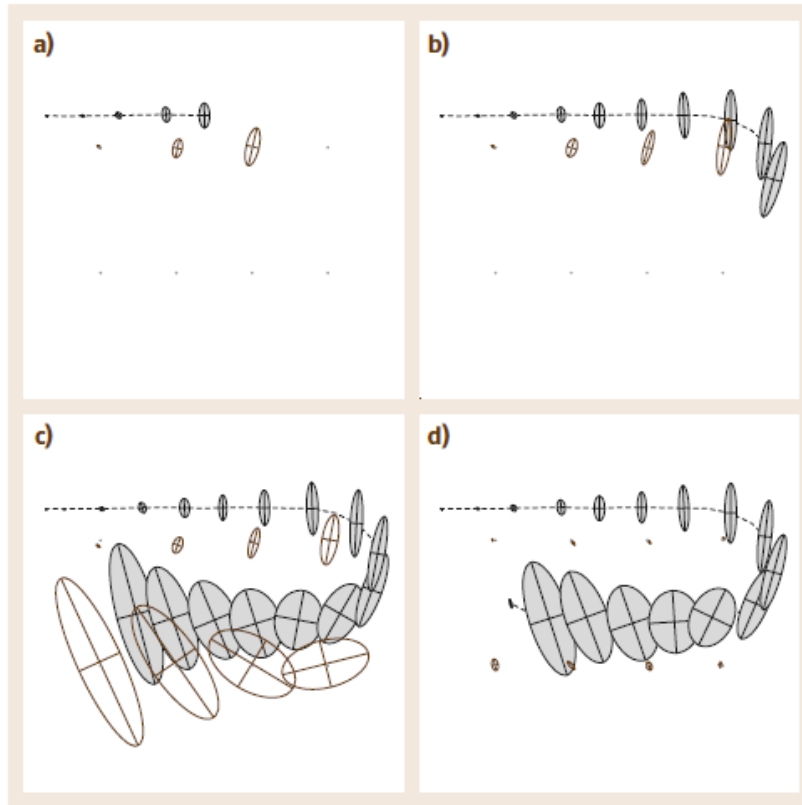


Fig.46.2a–d EKF applied to the online SLAM problem. The robot’s path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In **(a–c)** 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. 46.2a-d.

280. In Fig. 46.2a-d, the robot's route is depicted by the dotted line. Ex1005, 1157-58, Fig. 46.2a-d. The ellipses represent, each, a range of uncertainty (or equivalently "confidence") of the robot's location at each measurement point. Ex1005, 1157-58. The further the robot gets from the starting location, the more uncertain its location is, and thus the larger the ellipses. Ex1005, 1157-58. Landmarks and obstacles are represented by dots. Ex1005, 1157-58. The landmarks also have each their own uncertainty. Ex1005, 1157-58. Once the robot senses a landmark or pose for the second time, the uncertainty decreases for the entire environment map. Ex1005, 1157-58. This results in a more accurate map (mapping) and robot's poses (localization).

281. Therefore, it is my opinion that Stachniss discloses this limitation.

g) Element 2[b]: determining confidences associated with a respective one of the range of possible locations;

282. It is my opinion that Stachniss discloses this limitation.

283. As explained above with respect to Element 2[a] (*see supra* Section VII.B.1.f), Stachniss discloses that each node in the graph has an associated range corresponding to an uncertainty (or confidence) in the position of the node.

284. Stachniss further discloses determining confidences associated with a range. For example, Stachniss discloses a probability distribution (reproduced

below) of the location of a pose-node based on the uncertainty of the prior node and odometry sensor noise. Ex1005, 1155.

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

In the equation above, $\mathcal{N}$ denotes the 2-D normal (Gaussian) distribution with mean $g(x_{t-1}, u_t)$ and covariance matrix $\mathbf{R}_t$, wherein the covariance matrix represents a confidence measure. Ex1005, 1157 (disclosing “covariance matrix representing the uncertainty [(confidence measure)] in the[] estimates”).

285. Additionally, as discussed above in Section VII.B.1f, for a graph-SLAM method using sensor data, Stachniss discloses Equation 46.18 (reproduced below), which corresponds to the log of the posterior probability distribution that incorporates uncertainty (confidence measure), in the sensed environment feature data (e.g., visual sensor data), also denoted as feature observation data. Ex1005, 1163. In Equation 46.18, Stachniss shows the uncertainty (confidence measure) is represented in terms of the covariance matrices ($\mathbf{R}_t$ for the odometry reading and $\mathbf{Q}_t$ for the sensed environment features). Ex1005, 1157, 1163.

$$\begin{aligned} \log p(X_T, m | Z_T, U_T) = & \text{const} \\ & + \sum_t \underbrace{[x_t - g(x_{t-1}, u_t)]^T \mathbf{R}_t^{-1} [x_t - g(x_{t-1}, u_t)]}_{\text{odometry reading}} \\ & + \sum_t \underbrace{[z_t - h(x_t, m)]^T \mathbf{Q}_t^{-1} [z_t - h(x_t, m)]}_{\text{feature observation}} . \end{aligned} \quad (46.18)$$

286. Stachniss also discloses that each node has an uncertainty associated with its range of possible locations for both poses (nodes corresponding to robot's locations at which measurements are taken by at least one sensor, e.g., odometry sensor and/or vision sensor) and landmarks (environment features observed by robot from robot's locations (i.e, from the pose nodes)) as illustrated in Figure 46.2 (reproduced above). *See also* Ex1005, 1157–58 (disclosing in reference to Fig. 46.2 that “[a]s [robot] moves, its own pose uncertainty increases, as indicated by uncertainty ellipses of growing diameter [(confidence measure)]”), 1155, 1163. The diameter of each ellipse represent a measure of confidence associated with the range of the robot's possible locations at each measurement point. Ex1005, 1157–58.

287. A POSITA would have understood that, as discussed above, Stachniss discloses “confidence,” as described in the '325 Patent. For example, the '325 Patent says that “[t]he confidence can be based at least in part on the ranges,” Ex1001, 21:1–2, 47–49, “[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.

288. Therefore, it is my opinion that Stachniss discloses this limitation.

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

289. It is my opinion that Stachniss discloses this limitation.

290. For example, Stachniss explains with respected to graph-based techniques that “[m]odern SLAM systems often view the estimation problem as solving a sparse graph of constraints and applying nonlinear optimization to compute the map and the trajectory of the robot.” Ex1005, 1153–54, 1157, 1162. Stachniss further explains,

Graph-based methods address the full SLAM problem, hence are in the standard formulation not online. They draw their intuition form the fact that SLAM can be modeled by a sparse graph of soft constraints, where each constraint either corresponds to a motion or a measurement event. Due to the availability of highly efficient optimization methods for sparse nonlinear optimization problems, graph-based SLAM has become the method of choice for building large-scale maps. Recent developments have brought up several graph-based methods for incremental map building that can be executed at every time step during navigation. Data association search can be incorporated into the basic mathematical framework and different approaches that are even robust under wrong data associations are available today.

Ex1005, 1166.

291. Stachniss further explains that these optimizations are based at least in-part on the confidences. For example, Stachniss explains that the “quadratic form yields a sparse system of equations” which is then optimized. Ex1005, 1163. This quadratic form includes terms, such as R_t^{-1} and Q_t^{-1} , that are specifically directed towards the confidences of the nodes, as depicted in Equation 46.18 below. Ex1005,

1163; Ex1005, 1155–56 (explaining R_t and Q_t), 1157 (disclosing “covariance matrix representing the uncertainty in the [] estimates” and providing “the robot’s assessment [(confidence measure)] of its expected error” in the estimates).

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

292. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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.**

293. It is my opinion that Stachniss discloses this limitation.

294. As discussed previously with respect to Element 2[c] (*see supra* Section VII.B.1.h), Stachniss discloses generating a map from the optimized graph. Ex1005, 1153–54, 1157, 1162, 1166. Stachniss further discloses that SLAM methods have “been extended to situations with partial observability, with range-only [] or angle-only [] measurements.” Ex1005, 1158–59. Stachniss further discloses that the same landmark may be observed from multiple locations, providing additional information about its position, which a POSITA would have understood involves employing mathematics relating to rays and ray-tracing, as depicted in Fig. 46.7 (reproduced below).

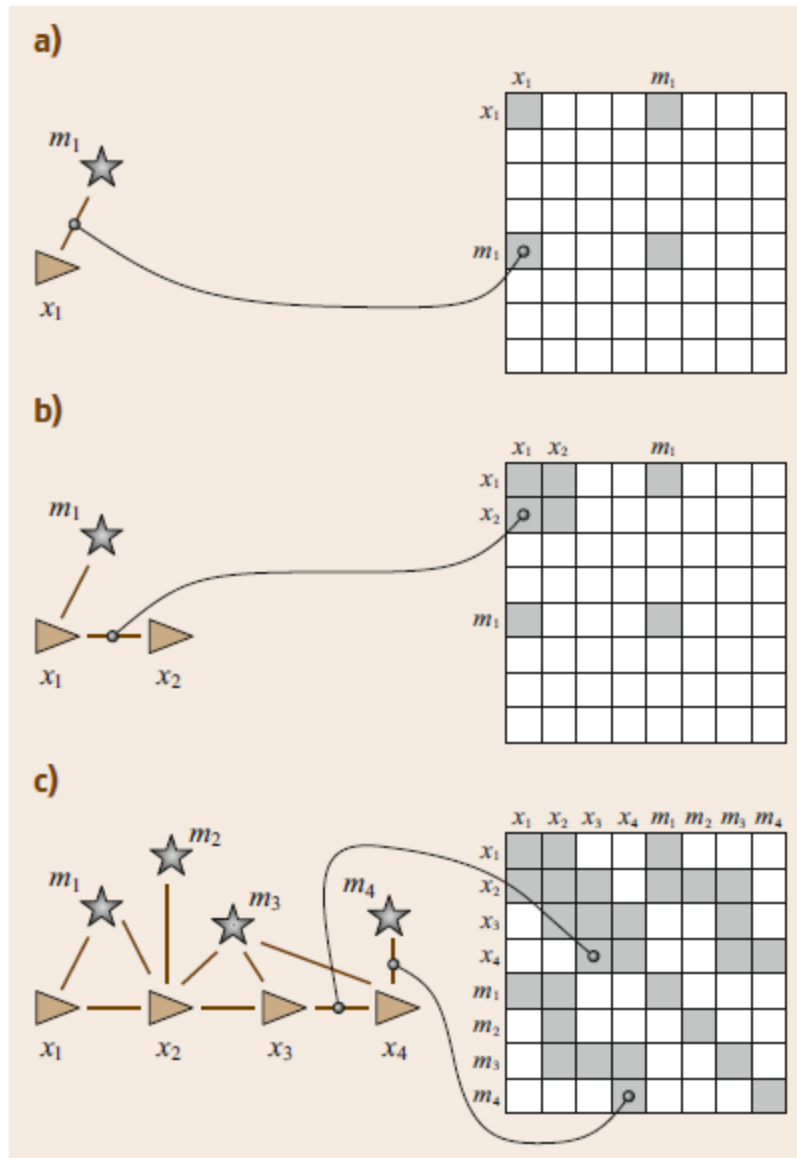


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7.

295. Stachniss further discloses that the generation of the map may comprise ray tracing with the scans generated by the sensor, the scans being associated with

the plurality of nodes. For example, Stachniss discloses map building with particle methods that comprise ray tracing. For example, Stachniss explains:

When a measurement z_t is received, two things happen: first, FastSLAM computes for each particle the probability of the new measurement z_t . Let the index of the sensed landmark be n . Then the desired probability is defined as follows

$$w_t^{[k]} = \mathcal{N}(z_t | x_t^{[k]}, \mu_{t,n}^{[k]}, \Sigma_{t,n}^{[k]}) . \quad (46.13)$$

The factor $w_t^{[k]}$ is called the importance weight, since it measures how important the particle is in the light of the new sensor measurement. As before, $\mathcal{N}$ denotes the normal distribution, but this time it is calculated for a specific value, z_t . The importance weights of all particles are then normalized so that they sum to 1.

Next, FastSLAM draws with replacement from the set of existing particles a set of new particles. The probability of drawing a particle is its normalized importance weight. This step is called resampling. The intuition behind resampling is that particles for which the measurement is more plausible have a higher chance of surviving the resampling process.

Finally, FastSLAM updates for the new particle set the mean $\mu_{t,n}^{[k]}$ and covariance $\Sigma_{t,n}^{[k]}$, based on the measurement z_t . This update follows the standard EKF update rules – note that the extended Kalman filters maintained in FastSLAM are, in contrast to EKF SLAM, all low-dimensional (typically 2-D).

Ex1005, 1159–60.

296. Stachniss further explains, with respect to occupancy graphs, that “FastSLAM has been extended in several ways. One set of variants are grid-based versions of FastSLAM, in which the Gaussians used to model point landmarks are replaced by an occupancy grid map [46.45–47]. The variant of [46.46] is illustrated

in Fig. 46.5.” Ex1005, 1161. Stachniss depicts a map generated using a FastSLAM with an occupancy grid in Fig. 46.5, reproduced below.

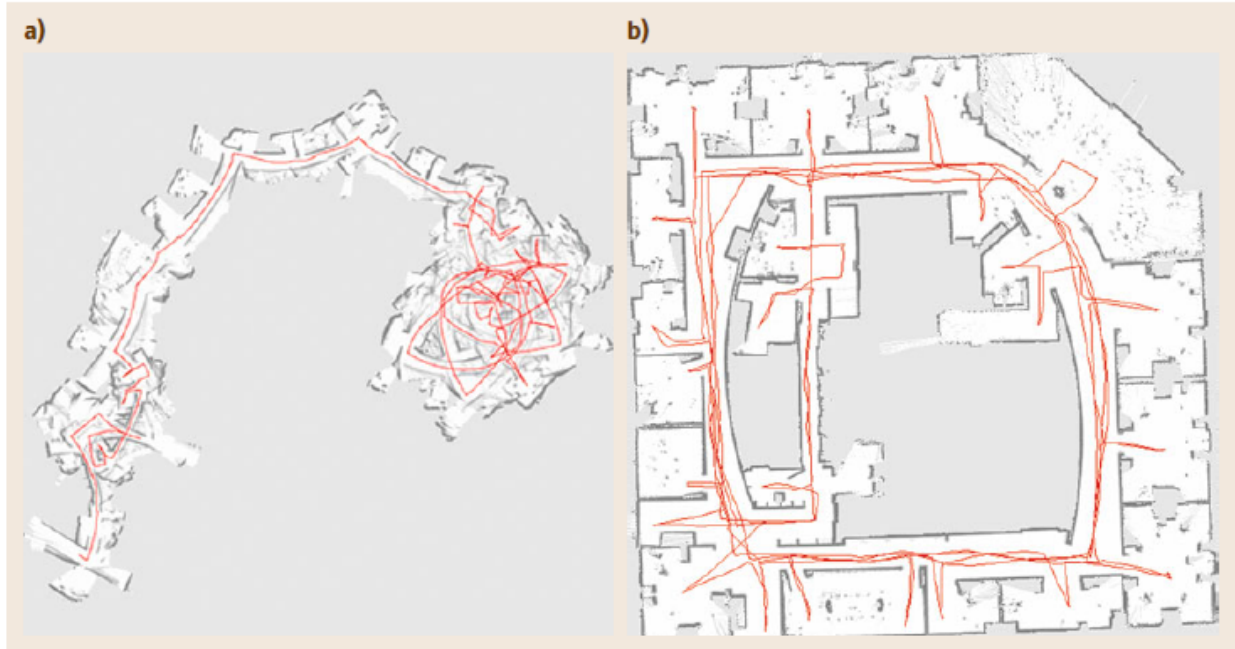


Fig. 46.5 Occupancy grid map generated from laser range data and based on pure odometry (image courtesy of Dirk Hähnel, University of Freiburg)

Ex1005, Fig. 46.5.

297. A POSITA would have understood updating an occupancy grid based on new sensor measurements, z_t , discloses ray-tracing as described in the '325 Patent. Ex1005, 1159–61; Ex1001, 22:22–34, Figure 10.

298. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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

299. It is my opinion that Stachniss discloses this limitation. As discussed with respect to Element 2[c] (*see supra* Section VII.B.1.h), Stachniss discloses optimizing the graph based at least in part on the confidences associated with each of the plurality of nodes.

300. Stachniss further discloses that the optimization comprises generating a cost function. For example, Stachniss explains that the log-posterior (representing a cost function to be optimized) may be represented in a quadratic form, as in Equation 46.18, reproduced below. Ex1004, 1163.

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

301. Stachniss further explains,

This quadratic form yields a sparse system of equations [a cost function] and a number of efficient optimization techniques can be applied. Common choices include direct methods such as sparse Cholesky and QR decomposition, or iterative ones such as gradient descent, conjugate gradient, and others. Most SLAM implementations rely on iteratively linearizing the functions g and h , in which case the objective [a cost function] in (46.18) becomes quadratic in all of its variables.

Ex1005, 1163.

302. As may be seen in Equation 46.18, the cost function is based at least in part on, for all t , x_t (the relative locations of each of the plurality of nodes), and R_t^{-1} and Q_t^{-1} (confidences associated with each of the plurality of nodes). Ex1005, 1154–56, 1163.

303. Therefore, it is my opinion that Stachniss discloses this limitation.

k) Element 3[b]: solving the cost function for a minimum value.

304. It is my opinion that Stachniss discloses this limitation.

305. For example, Stachniss explains,

If we think of the graph as a spring-mass model [46.60], computing the SLAM solution is equivalent to computing the state of *minimal energy* [minimum value] of this model. To see, we note that the graph corresponds to the log-posterior of the full SLAM problem (46.4).

Ex1005, 1163.

306. With respect to the “sparse system of equations” (cost function) discussed above with respect to Element 3[a] (*see supra* Section VII.B.1.j), Stachniss discloses that the system may be optimized with “a number of efficient optimization techniques,” and that “[c]ommon choices include direct methods such as sparse Cholesky and QR decomposition, or iterative ones such as *gradient descent* [for cost function minimization], conjugate gradient, and others.” Ex1005, 1163.

307. A POSITA would have recognized that Stachniss discloses function-minimization techniques, and Stachniss thereby discloses that the cost function is solved for a minimum value.

308. Therefore, it is my opinion that Stachniss discloses this limitation.

I) 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.

309. It is my opinion that Stachniss discloses this limitation.

310. Stachniss explains that SLAM methods estimate position based on measures of movement, like odometry, and sensor measurements (observations) of landmarks by the robot at each of its positions. Ex1005, 1154–55. These estimates are the most-probable locations given all the data available to the robot. Ex1005, 1155, 1163. As Stachniss explains, these most-probable locations are best thought of as the peak of a probabilistic distribution associated with each node, which corresponds to the mean or center for a Gaussian probabilistic distribution. Ex1005, 1155. For example, Stachniss discloses a probability distribution (reproduced below) of the location of a pose-node based on the uncertainty of the prior node and odometry sensor noise. Ex1005, 1155.

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

In the equation above, $\mathcal{N}$ denotes the 2-D normal (Gaussian) distribution with mean $g(x_{t-1}, u_t)$ and covariance matrix $\mathbf{R}_t$. Stachniss further discloses:

In SLAM, it is common to think of those mathematical models as probability distributions: $p(x_t | x_{t-1}, u_t)$ characterizes the probability distribution of the location x_t assuming that a robot started at a known location x_{t-1} and measured the odometry data u_t . And likewise, $p(z_t | x_t, m)$ is the probability for measuring z_t if this measurement is taken at a known location x_t in a known environment m . Of course, in the SLAM problem we do *not* know the robot location, and neither do we know the environment. As we shall see, Bayes rule takes care of this, by transforming these mathematical relationships into a form where we can recover probability distributions over those latent variables from the measured data.

Ex1005, 1155.

311. Stachniss further explains with respect to graph-based SLAM that “the graph corresponds to the log-posterior [probabilistic distribution] of the full SLAM problem” and that the solution is the one that maximizes the log-posterior probabilistic distribution. Ex1005, 1163; Equation 46.17.

312. Stachniss further discloses that the probabilistic function of the full SLAM problem can be expressed in terms of the nodes’ probabilistic distributions, wherein a probability distribution at each pose node in the graph corresponds to a surrounding region around its corresponding pose node, wherein the surrounding region represents the possible locations of the true positions of the robot. Ex1005, 1155, 1157–58, 1163, Fig. 46.2a–d (showing surrounding region around each node as ellipse), Equations (46.16)-(46.18). Stachniss explains that “in the SLAM problem we do not know the robot location. . . . Bayes rule takes care of this, by

transforming these mathematical relationships into a form where we can recover probability distributions over those latent variables [(e.g., robot's positions x_i)] from the measured data.” Ex1005, 1155. Stachniss further depicts this surrounding region (or range) around each node in Figure 46.2, where “[t]he robot's path is a *dotted line*, and its estimates of its own positions are *shaded ellipses* [(ranges corresponding to probabilistic distributions)].” Ex1005, 1158, Fig. 46.2a-d. When additional information allows the robot to reduce the uncertainty associated with each node, the surrounding region (range) corresponding to the associated probabilistic distribution decreases (indicating an increase in the associated confidence), as depicted in Fig. 46.2a–d (reproduced below). Ex1005, 1158.

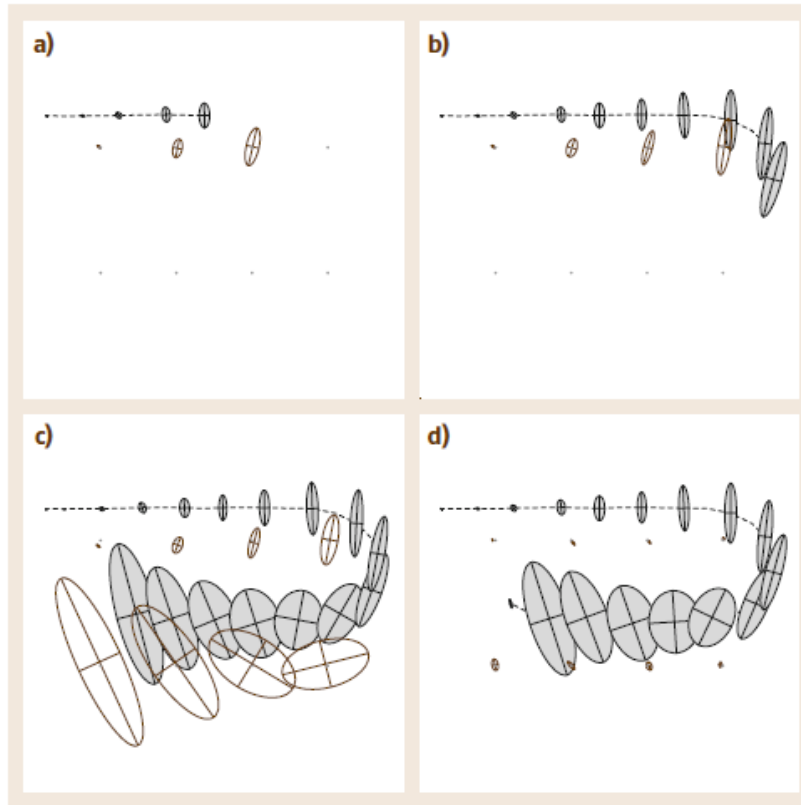


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the 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. 46.2a-d.

313. Therefore, it is my opinion that Stachniss discloses this limitation.

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.**

314. It is my opinion that Stachniss discloses this limitation.

315. As discussed above with respect to Element 1[d] (*see supra* Section VII.B.1.e), Stachniss discloses constraining of the graph between a start location and end location, the start and end locations being at a substantially similar location in the environment.

316. Stachniss further discloses determining the robot returned to a start position based on detecting a home locator in the environment. Specifically, Stachniss discloses loop closing based on the detection of features in the environment. Ex1005, 1157–59. “The ability to close loops is a key characteristic of modern-day SLAM algorithms” because of the helpful effect of loop closing on reducing the uncertainty in the mapping and localization. Ex1005, 1156. Further, loop closing is possible when the robot “reach[es] the *same location* from multiple directions.” Ex1005, 1156. Stachniss explains that a robot starts at an initial location (home location), x_0 , which position may be known precisely. Ex1005, 1154, 1157–59. At x_0 , as at every node, the robot may “sense[] objects in the environment.” Ex1005, 1154. When the robot encounters those objects again later in its route, it

can associate later measurements with earlier measurements and thereby determine that it has returned to its initial position. Ex1005, 1158, 1161. Stachniss further explains that loop closing may be enhanced by visual sensors, which can use “appearance information” to detect features in the environment associated with the start location. Ex1005, 1166, 1168. Such features are “home locators.”

317. Stachniss also discloses methods to verify that a loop closure is correct based on its effect on the graph in addition to the appearance of the home locator, according to a "soft correspondence constraint" that can be integrated into the cost function to be optimized. Ex1005, 1164. The robot may propose an appearance correspondence between a first landmark and a second landmark (home locators), for example when the robot determines that they are visually similar. Ex1005, 1164, 1166, 1168. The robot then tests the correspondence between the locations of these landmarks by including an additional cost to the optimization function, associated with the correspondence between the locations being incorrect. Ex1005, 1164. This is depicted in equation 46.19 (reproduced below), wherein the cost or penalty is introduced through the diagonal matrix Γ .

$$(m_j - m_i)^T \Gamma (m_j - m_i) . \quad (46.19)$$

318. In this way, Stachniss discloses that its system can determine and verify that it has returned to its start position by detecting landmarks (home locators) in the environment.

319. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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.**

320. It is my opinion that Stachniss discloses this limitation.

321. For example, Stachniss discloses that SLAM methods may be active or passive, wherein passive algorithms require navigating the robot under user control. Ex1005, 1156. Stachniss explains,

In passive SLAM algorithms, some other entity 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, and pursue arbitrary motion objectives. In active SLAM, the robot actively explores its environment in the pursuit of an accurate map. Active SLAM methods tend to yield more accurate maps in less time, but they constrain the robot motion. There exist hybrid techniques in which the SLAM algorithm controls only the pointing direction of the robot's sensors, but not the motion direction.

Ex1005, 1156.

322. Stachniss's disclosure of a robot that gives the robot designer the freedom to implement arbitrary motion controllers and objectives discloses the robot navigating the environment under user control. Ex1005, 1162.

323. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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;**

324. It is my opinion that Stachniss discloses this limitation.

325. As explained above with respect to Elements 1[b] and 1[c] (see *supra* Sections VII.B.1.c–d), Stachniss discloses that each position of the robot is represented by a node in a graph, and that the graph comprises extended scan groups. *See* §§ VII.B.1.c–d. Further, Stachniss discloses “[a] mobile robot roams an unknown environment, starting at an initial location x_0 The initial location x_0 [root node] often serves as a *point of reference* for the estimation algorithm.” Ex1005, 1154. Stachniss also discloses that “it is common to think of those mathematical models ... assuming that a robot started at a known location.” Ex1005, 1155.

326. Stachniss also discloses that the position of the robot is relative to the landmarks in the environment. In the pose graph, each landmark i ($i=1, \dots, N$) is labeled m_i , and each robot position at a time t ($t=0, \dots, T$) is labeled x_t . Ex1005, 1154, 1162–63. This is demonstrated in Figure 46.7a–c, reproduced below.

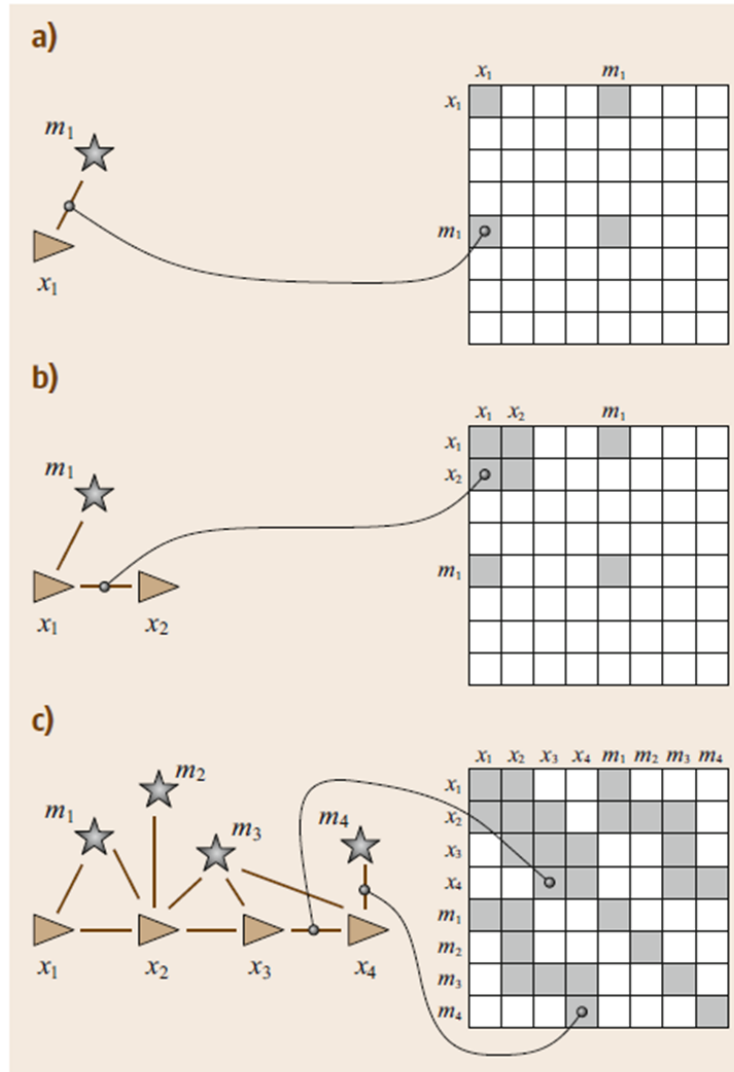


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a–c.

327. A POSITA would have understood that disclosure of use of the initial location as a root node to be used as a reference location for the graph also discloses use of the initial location as a root node to be used as a reference location for each of the extended scan groups.

328. Therefore, it is my opinion that Stachniss discloses this limitation.

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 node [sic] is different from the respective node; and

329. It is my opinion that Stachniss discloses this limitation.

330. As explained above with respect to Element 1[c] (*see supra* Section VII.B.1.d), Stachniss discloses scan-matching based on overlap in measurements of distinct features in scans taken at at least two of the respective nodes. Ex1005, 1165–69. For example, Stachniss discloses the use of “visual odometry” based on feature detection and tracking across images (scans taken at two or more pose nodes) to find the overlapping features between these images and, subsequently, use the determined overlap to estimate the distance between two pose-nodes. Ex1105, 1168.

331. Stachniss further discloses that its method may find overlap in measurements from at least two of the respective nodes, where the root node is different from the respective nodes. For example, Stachniss discloses a simplified pose-landmark graph in Fig. 46.7a–c, reproduced below, wherein x_1 is the initial pose-node (root node), and each of x_2 , x_3 , and x_4 (at least two of the respective nodes) are nodes in an extended scan group that detect the same landmark (*i.e.*, find overlap in measurement of distinct features), m_3 . Ex1005, 1164.

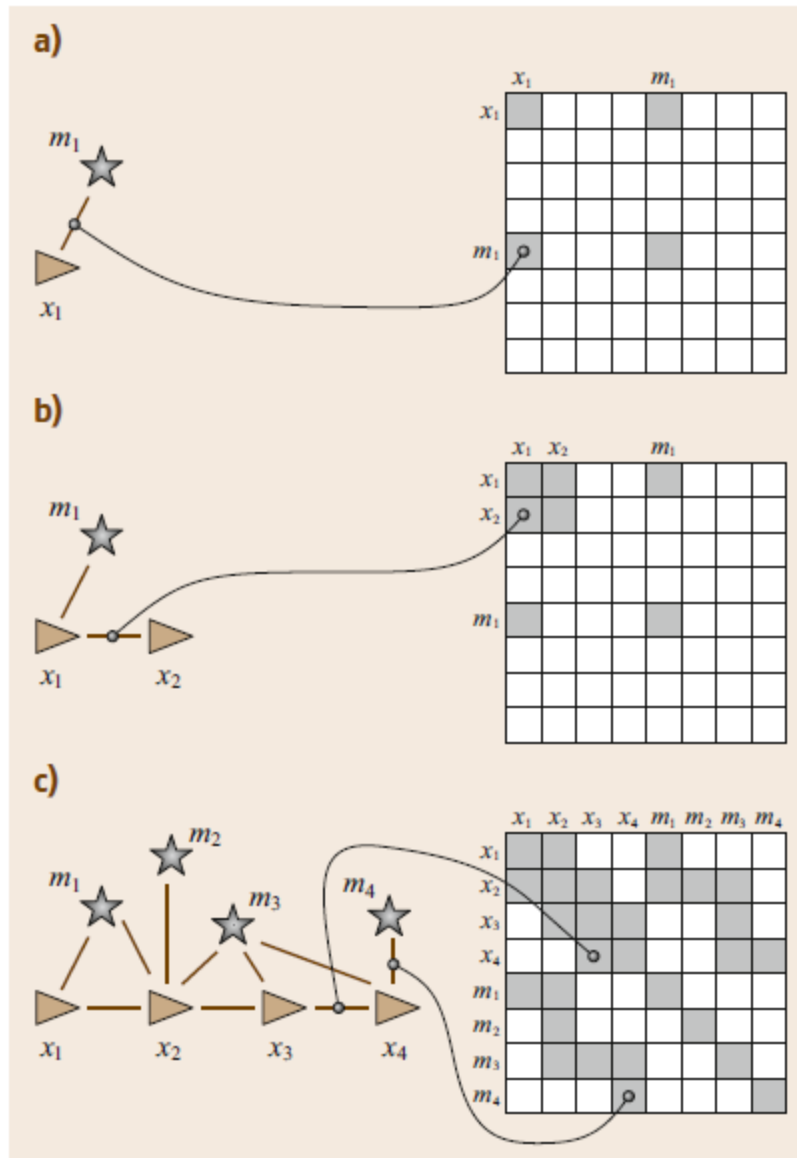


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7.

332. As also explained above with respect to Element 1[c] (*see supra* Section VII.B.1.d), Stachniss also discloses hierarchical methods which divide large maps into independent local maps (extended scan groups). Ex1005, 1163–64. A POSITA

would have understood that a local map consisting of only a single node would not be useful, and, therefore, would have understood that Stachniss's disclosure of local maps discloses at least two of the respective nodes of the plurality of nodes, the root node is different from the respective node.

333. Therefore, it is my opinion that Stachniss discloses this limitation.

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.

334. It is my opinion that Stachniss discloses this limitation.

335. For example, as explained above with respect to Elements 1[c] and 7[b] (*see supra* Sections VII.B.1.d, p), Stachniss depicts grouping three nodes into an extended scan group based on mutual detection of a landmark in Fig. 46.7a–c, reproduced below (e.g., detection of the same landmark m_3 at pose nodes x_2, x_3, x_4). The extended scan group may be represented by the vector drawn from the m_3 column in the sparse matrix representation of the graph constraints as depicted in Fig. 46.7a–c.

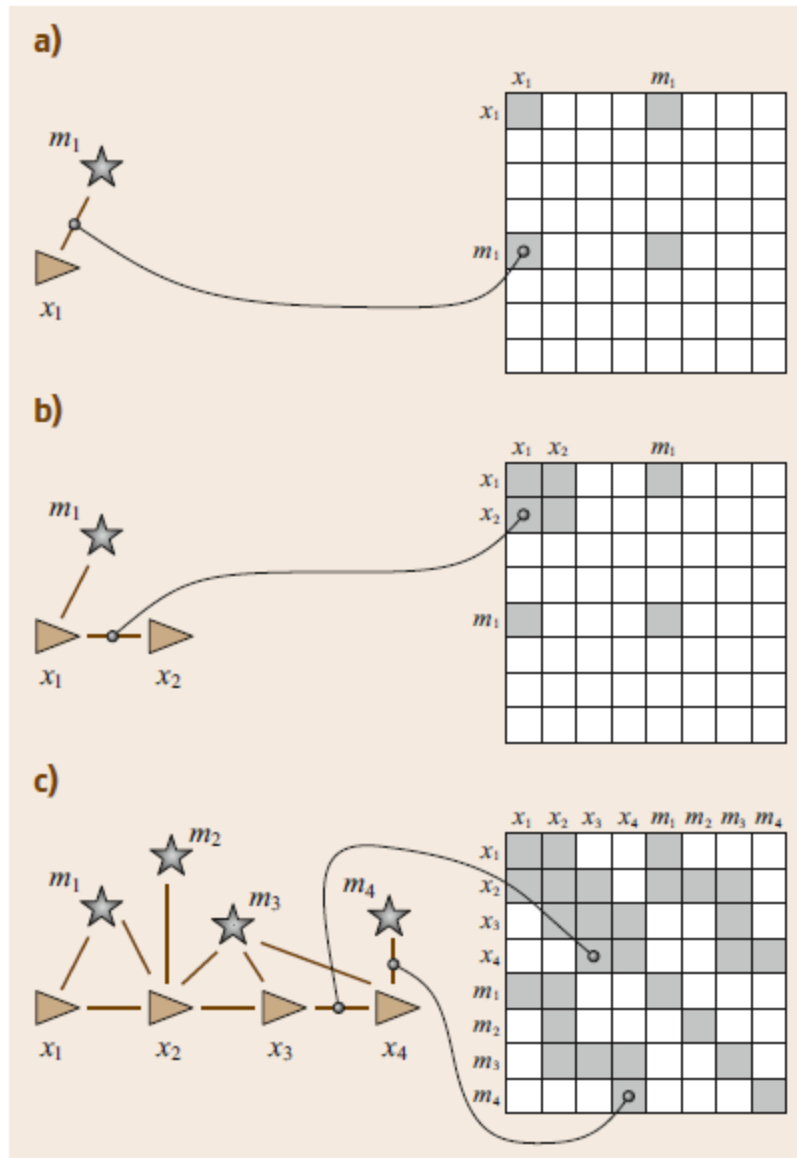


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7.

336. As a further example, Stachniss discloses the use of hierarchical methods, which use independent local maps (extended scan groups). Ex1005, 1164. Stachniss further discloses that these local maps are constructed based on

overlapping features, for example explaining that maps “are merged in case of re-visiting a place,” e.g., as determined by visual sensors. Ex1005, 1164. Stachniss further explains that others have implemented hierarchical methods based on visual sensors, such as “stereo and Kinet-style cameras,” which “[c]ombine[] local bundle adjustment [extended scan groups] with sparse global optimization for on-the-fly processing.” Ex1005, 1165.

337. Therefore, it is my opinion that Stachniss discloses this limitation.

r) Element 8[pre]: A robot, comprising:

338. To the extent the preamble is limiting, it is my opinion that Stachniss discloses it.

339. Stachniss discloses a robot that simultaneously maps an environment as it travels through that environment. Ex1005, 1153–1154. Specifically, Stachniss attempts to solve what it calls the SLAM problem. Ex1005, 1153–54. SLAM stands for simultaneous localization and mapping. Ex1005, 1153.

The SLAM problem is defined as follows: A mobile robot roams an unknown environment, starting at an initial location x_0 . Its motion is uncertain, making it gradually more difficult to determine its current pose in global coordinates. As it roams, the robot can sense its environment with a noisy sensor. The SLAM problem is a problem of building a map of the environment while simultaneously determining the robot’s position relative to this map given noisy data.

Ex1005, 1154.

340. Stachniss discloses a system that solves the SLAM problem.

[Stachniss] reviews three basic SLAM paradigms, from which most others are derived. The first, known as EKF SLAM, is in robotics historically the earliest but has become less popular due to its limiting computational properties and issues resulting from performing single linearizations only. The second approach uses nonparametric statistical filtering techniques known as particle filters. It is a popular method for online SLAM and provides a perspective on addressing the data association problem in SLAM. The third paradigm is based on graphical representations and successfully applies sparse nonlinear optimization methods to the SLAM problem. It is the main paradigm for solving the full SLAM problem and recently also incremental techniques are available.

Ex1005, 1157.

341. These paradigms “address[] the problem of acquiring a spatial map of an environment while simultaneously localizing the robot relative to this model.”

Ex1005, 1153.

342. Stachniss discloses a robot that stores the sequence of the robot’s locations (robot’s path) in a set, X_T , consisting of a sequence of three-dimensional vectors $x_0, x_1, x_2, \dots, x_T$, wherein a three-dimensional vector x_t corresponds to the location (e.g., 2D position and orientation for a robot traveling on a flat ground) of the robot at time t . Stachniss further explains that the relative motion of the robot between two consecutive locations along the path is characterized by a sequence of odometry measurements $u_1, u_2, \dots, u_T$, stored in a set U_T , wherein u_t characterizes the relative motion of the robot between time $t-1$ and t . Stachniss further explains that, as the robot moves, the robot records, at each of its locations x_t , through its sensor(s), a sequence of measurements z_t of objects (or features) in the environment

and these measurements z_t are stored in a set Z_T . Ex1005, 1154, 1160, 1162–66, Fig. 46.1, Fig. 46.3, Fig. 46.7a–c. Stachniss further explains that the robot collects this information as it travels through an environment and simultaneously uses the information to create the “best estimate for the map” of the environment. Ex1005, 1163. The robot uses the estimated map to travel along a route. Ex1005, 1153–1154. For example, Stachniss explains that maps developed in real-time allow robots to autonomously “explore[] its environment in pursuit of a more accurate map.” Ex1005, 1156; *see also* Ex1005, 1164 (“[I]ncremental optimization techniques have been proposed that aim at providing a sufficient but not necessarily perfect model of the environment at every point in time. This allows a robot to make decisions based on the current model, for example, to *determine exploration goals.*”).

343. Therefore, it is my opinion that Stachniss discloses this limitation.

- 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**

344. In my opinion, Stachniss discloses this limitation.

345. This limitation was addressed in the discussion of Element 1[b], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.c.

t) Element 8[b]: a mapping and localization unit configured to execute computer readable instructions to:

346. It is my opinion that Stachniss discloses this limitation.

347. For example, Stachniss discloses that “[r]obots that do all computations onboard have limited resources in memory and computation power.” Ex1005, 1157. The robot receives information from sensors and calculates and stores map information while moving through an environment. Ex1005, 1153–55, 1162–66.

348. Stachniss further discloses a “graphical processing unit (GPU)” that allows for processing a three-dimensional map. Ex1005, 1169. Stachniss also discloses a robot processing data and implementing mathematical models for mapping and localization, which means the robot must have a processing device configurable to execute the computer readable instructions. Ex1005, 1154–1155, 1157–66. Stachniss also explicitly refers to a processor when it states that the robot can “process all data at the same time” for full SLAM, can “execute” an incremental optimization scheme “at each step during mapping”, and can perform “relative optimization . . . aim[ed] at computing locally consistent geometric maps.” Ex1005, 1155, 1164–65.

349. A POSITA would have understood that disclosure of computer memory and processors to perform mapping and localization tasks disclose a means for mapping and localization, *i.e.*, a mapping and localization unit.

350. Therefore, it is my opinion that Stachniss discloses this limitation.

- u) Element 8[b][1]: generate a graph of the plurality of nodes based at least in part on the generated scans;**

351. In my opinion, Stachniss discloses this limitation.

352. This limitation was addressed in the discussion of Element 1[b], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.c.

- v) Element 8[b][2]: determine extended scan groups in-part on at least two or more nodes of the plurality of nodes;**

353. In my opinion, Stachniss discloses this limitation.

354. This limitation was addressed in the discussion of Element 1[c], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.d.

- w) Element 8[b][3]: perform scan matching on the extended scan groups; and**

355. In my opinion, Stachniss discloses this limitation.

356. This limitation was addressed in the discussion of Element 1[c], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.d.

- 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.**

357. In my opinion, Stachniss discloses this limitation.

358. This limitation was addressed in the discussion of Element 1[d], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.e.

- 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.**

359. In my opinion, Stachniss discloses this limitation.

360. This limitation was addressed in the discussion of Element 2[b], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.g.

- 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.**

361. In my opinion, Stachniss discloses this limitation.

362. This limitation was addressed in the discussion of Claim 3, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.j–k.

- 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.**

363. In my opinion, Stachniss discloses this limitation.

364. This limitation was addressed in the discussion of Element 2[d], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.i.

**bb) Claim 12: The robot of claim 8, further comprising:
an actuator configured to move the robot between
locations in the environment.**

365. In my opinion, Stachniss discloses this limitation.

366. This limitation was addressed in the discussion of Element 1[a], and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.b.

**cc) Claim 13: The robot of claim 8, further comprising: a
user interface for controlling the robot by at least one
user.**

367. It is my opinion that Stachniss discloses this limitation.

368. As explained above with respect to Claim 6 (*see supra* Section VII.B.1.n), Stachniss discloses that a robot with mapping functionalities may be advantageously under the control of a user. Ex1005, 1156. Stachniss further discloses that a user may exert control with “*arbitrary motion controllers*” (a user interface for controlling the robot by at least one user). Ex1005, 1156. Further, a POSITA would have understood that disclosure of a robot operating under the navigational control of a user also discloses a means for the user to exercise that control, *i.e.*, a user interface.

369. Therefore, it is my opinion that Stachniss discloses this limitation.

**dd) Claim 14: The robot of claim 8, further comprising: a
navigation unit configured to navigate the robot
autonomously without the user.**

370. It is my opinion that Stachniss discloses this limitation.

371. As discussed above with respect to Element 8[b] (*see supra* Section VII.B.1.t), Stachniss discloses a robot with a processor and memory to execute robotic functions including navigation functions (a navigation unit).

372. Stachniss further discloses that robotic SLAM may be implemented with passive and active methods, wherein robots implementing active SLAM methods comprise a navigation unit configured to navigate the robot autonomously without the user. Stachniss explains,

In passive SLAM algorithms, some other entity 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, and pursue arbitrary motion objectives. In active SLAM, the *robot actively explores its environment* [navigates autonomously without the user] in the pursuit of an accurate map. Active SLAM methods tend to yield more accurate maps in less time, but they constrain the robot motion. There exist hybrid techniques in which the SLAM algorithm controls only the pointing direction of the robot's sensors, but not the motion direction.

Ex1005, 1156.

373. Therefore, it is my opinion that Stachniss discloses this limitation.

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:

374. To the extent the preamble is limiting, it is my opinion that Stachniss discloses it.

375. As discussed above with respect to Element 8[b] (*see supra* Section VII.B.1.t), Stachniss explicitly states that “[r]obots that do all computations onboard

have limited resources in memory and computation power.” Ex1005, 1157. The robot receives information from sensors and calculates and stores map information while moving through an environment. Ex1005, 1153–55, 1162–66. Stachniss discloses a “graphical processing unit (GPU)” that allows for processing a three-dimensional map. Ex1005, 1169. Stachniss also discloses a robot processing data and implementing mathematical models, which means the robot must have a processing device configurable to execute the computer readable instructions. Ex1005, 1154–1155, 1157–62.

376. Stachniss also explicitly refers to a processor when it states that the robot can “process all data at the same time” for full SLAM, can “execute” an incremental optimization scheme “at each step during mapping”, and can perform “relative optimization . . . aim[ed] at computing locally consistent geometric maps.” Ex1005, 1155, 1164–65.

377. A POSITA would have understood that the robots disclosed in Stachniss capable of implementing the solution(s) disclosed in Stachniss would have a computer-readable medium having computer readable instructions stored thereon, that when executed by at least one processor, configure the at least one processor to perform the actions described in the remainder of the claim.

378. Therefore, it is my opinion that Stachniss discloses this limitation.

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;**

379. It is my opinion that Stachniss discloses this limitation.

380. As explained above with respect to Element 1[b] (*see supra* Section VII.B.1.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. Further, as explained above with respect to Elements 8[b] and 15[pre] (*see supra* Sections VII.A.1.t, ee), the robot comprises a memory and processor that provide a means for the robot to map and navigate an environment using these sensors. A POSITA would have understood that these memory and processors control the manner in which scans are generated in association with the location in the environment by transmitting a signal to the at least one sensor to generate scans of the environment. This is consistent with the Written Description of the '325 Patent, which discloses that “[c]ontroller 254 can send and/or receive signals, such as power signals, control signals, sensor signals, interrogatory signals, status signals, data signals, electrical signals and/or any desirable signals” and that “[c]ontroller 254 can include one or more processors (e.g., microprocessors) and other peripherals” with “[m]emory 252 [] provid[ing] instructions and data to controller 254” and “[a]ccordingly, controller 254 can perform logical and arithmetic operations based on program instructions stored within memory 252.”

Ex1001, 7:49–21, 8:33–36.

381. Therefore, it is my opinion that Stachniss discloses this limitation.

gg) Element 15[b]: generate a graph of the plurality of nodes based in-part on the generated scans;

382. In my opinion, Stachniss discloses this limitation.

383. This limitation was addressed in the discussion of Elements 1[b] and 8[b][1], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.c, u.

hh) Element 15[c]: determine extended scan groups based at least in part on two or more nodes of the plurality of nodes;

384. In my opinion, Stachniss discloses this limitation.

385. This limitation was addressed in the discussion of Elements 1[c] and 8[b][2], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.d, v.

ii) Element 15[d]: perform scan matching on the extended scan groups; and

386. In my opinion, Stachniss discloses this limitation.

387. This limitation was addressed in the discussion of Elements 1[c] and 8[b][3], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.d, w.

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.

388. In my opinion, Stachniss discloses this limitation.

389. This limitation was addressed in the discussion of Elements 1[d] and 8[b][4], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.e, x.

kk) Claim 16: The non-transitory computer-readable medium of claim 15, wherein each extended scan group includes at least three or more scans.

390. It is my opinion that Stachniss discloses this limitation.

391. As discussed above with respect to Element 1[c] and Claim 7 (*see supra* Sections VII.B.1.d, o–q), Stachniss discloses extended scan groups.

392. Stachniss further discloses each extended scan group includes at least three or more scans. For example, Stachniss depicts in Figure 46.7a–c, reproduced below, a pose-landmark graph wherein the extended scan group consists of pose-nodes x_2 , x_3 , x_4 each comprising a scan of the same landmark m_3 (at least three or more scans) in Figure 46.7a–c, reproduced below.

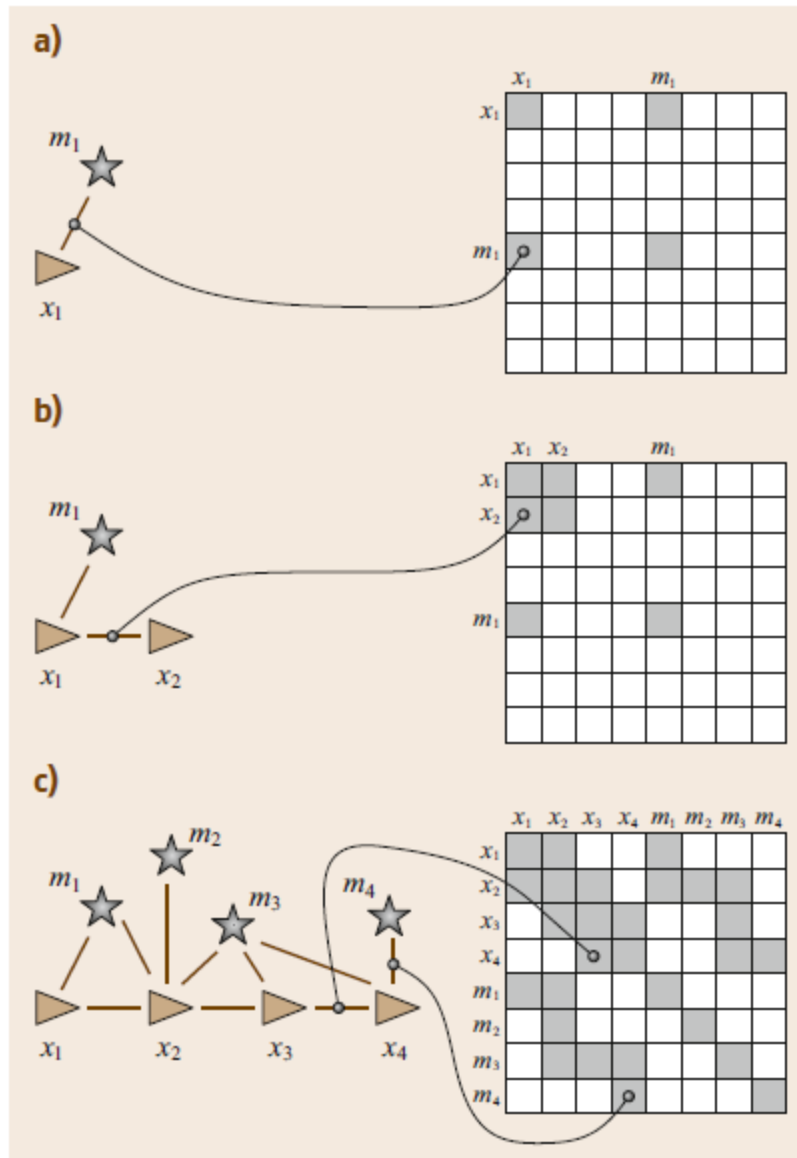


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a-c.

393. Therefore, it is my opinion that Stachniss discloses this limitation.

II) 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.

394. It is my opinion that Stachniss discloses this limitation.

395. This limitation was addressed in the discussion of Element 3[a] and Claim 10, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.j, z.

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.

396. It is my opinion that Stachniss discloses this limitation.

397. This limitation was addressed in the discussion of Element 3[b] and Claim 10, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.k, z.

C. Grounds 3 and 4: Claims 1–18 are Rendered Obvious in View of Olson or Stachniss in Combination with Fong

398. It is my opinion that to the extent that either Olson or Stachniss does not disclose claims 1–18, then it would have been obvious to combine those references with Fong to render each claim obvious.

1. Motivation to Combine Olson or Stachniss with Fong

399. A POSITA would have been motivated to combine Olson or Stachniss with Fong. Specifically, a POSITA would have been motivated to use the mapping

algorithm disclosed in Olson or Stachniss with the autonomous cleaning robot disclosed in Fong because Fong discloses a robotic system including features, such as a memory, processor, sensor, motor, controller, and mapping/navigation system that would be required to carry out the methods disclosed in Olson or Stachniss. Ex1006, 5:9–44, 6:20–36. Fong discloses a robot that includes a mapping/navigation system, but does not provide the details of how to implement such a mapping/navigation system. Ex1006, 5:9–44. Referring to the mapping/navigation system, Fong states that “[a]ny suitable technique and components may be used to localize and register the robot 200, such as machine vision (e.g., using the camera 270B and Feature Recognition or Class Recognition software).” Ex1006, 6:26–34. A POSITA would have looked to Olson or Stachniss to obtain the details of how to implement such a mapping/navigation system. It would have been obvious for a POSITA to use the mapping/navigation methods described in Olson or Stachniss, especially as there was a limited number of mapping/navigation methods available at the time. Ex1004, 56–60; Ex1005, 1157–1166. Therefore, it is my opinion that it would have been obvious to a POSITA to combine Olson or Stachniss with Fong.

400. Furthermore, the references all state that it would be beneficial to combine the disclosed methods with others. For example, Olson explains that it should be combined with an autonomous robot, like the robot described in Fong.

Ex1004, 9. Stachniss is a reference guide and was meant to be implemented by people in the robotics field. In addition, Fong discloses that a user should rely on SLAM techniques, like those in Olson or Stachniss, to map an environment. Ex1006, 6:26–36, 7:31–60, 8:24–40; Ex1004, 9–16, 55–72, 89–96; Ex1005, 1157–69. Therefore, it is my opinion that a POSITA would have had a reasonable expectation of success in combining Olson or Stachniss with Fong.

2. Element-by-Element Analysis

401. My element-by-element analysis is as follows.

- a) **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.**

402. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Fong or Stachniss in view of Fong discloses it.

403. Fong explicitly discloses:

In some embodiments, or in the invention, the robot 200 takes new images of the dock 600 and processes it as described above with respect to the database of modeled images to determine real or near-real time coordinates of the robot 200 with respect to the pose of the dock 600.

Ex1006, 13:38–42.

404. Further, Fong discloses that the robot is able to find the dock and to determine if it returned to the dock by detecting fiduciary markers (home locators):

[T]he fiducial markers **640A**, **640B** are configured to define a pose of the robot dock **600** (FIG. 6; Block **300**). For example, the fiducial markers **640A**, **640B** may have a predetermined spatial relationship with respect to one another and/or to a reference on the docking station **600** and/or to a planar surface directly beneath the dock **600**. As described herein, the fiducial markers **640A**, **640B** may be used by the pose sensor assembly **270A-270B** of the mobile robot **200** in order to determine a pose of the docking station **600** (FIG. 6 (Block **302**)) and/or to map out a docking path **180** (FIGS. 4A-4C; FIG. 6 (Block **304**)). The docking path **180** may be used to provide instructions to the robot **200** to maneuver the robot **200** to the dock **600**, for example, so that the robot **200** may connect with locks, clamps or detents **620A**, **620B**, or with electrical contacts **622A**, **622B** of the docking port **660** to charge a battery. The docking path **280** may be used to provide instructions that maneuver the robot **200** to align its air path with a docking lane or path such as an evacuation collar **610** on the dock **600** such that the dock moves debris from the robot **200** into the debris receptacle **670** of the dock **660**. The evacuation collar **610** (or mating collar) is shown in FIGS. 4D and 4E as being positioned such that the robot **200** will be positioned above the evacuation collar, but the invention contemplates the robot **200** aligning with a mating collar **610** positioned above or beside the robot **200** as well. The fiducial markers **640A**, **640B** may be any feature that is configured to be used for pose detection. For example, the fiducial markers **640A**, **640B** may be a photogrammetry target, two or more lights such as LEDs, a spatially recognizable pattern, or a bar code.

Ex1006, 4:45–5:8.

405. It is also my opinion that it would have been obvious to a POSITA to combine Olson or Stachniss with Fong. A POSITA would have known that it would be beneficial for an autonomous robot as described in each of Olson and Stachniss to know that it arrived back at its home locator so it could recharge itself. A POSITA would also have had a reasonable expectation of success as each of Olson and Stachniss is directed to allowing a robot to recognize its environment from a set

starting location and returning to the same location in order to “close the loop.” This functionality goes hand-in-hand with returning to a dock as described in Fong.

406. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong renders this limitation obvious.

b) Element 8[b]: a mapping and localization unit configured to execute computer readable instructions to:

407. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Fong or Stachniss in view of Fong discloses it.

408. Fong explicitly discloses a mapping/navigation system, *i.e.*, a mapping and localization unit. For example, Fong discloses:

The mobile robot **200** may be any suitable robot and it will be appreciated that not all of the components, features and functionality described herein are required in all embodiments of the invention. With reference to **FIG. 3**, the exemplary mobile robot 200 includes a chassis **210**, a controller **220**, memory **222**, a battery **224**, a battery charger **226**, a human-machine interface (HMI) **228**, a drive system **230**, **a mapping/navigation system 240**, a service operation system **242**, a wireless communication system 250, an IR emitter **260**, and pose sensors **270A-B**. The mobile robot **200** may be generally configured in the manner of or include features from the Roomba™ floor cleaning robot and/or robots as described in U.S. Pat. No. 7,024,278 and U.S. Published Application No. 2007/0250212, the disclosures of which are incorporated herein by reference, with suitable modifications.

Ex1006, 5:9–25; *see also* Ex1006, 5:26–36, 6:26–29, 8:28–32.

409. Fong depicts this unit in Figure 3, reproduced below.

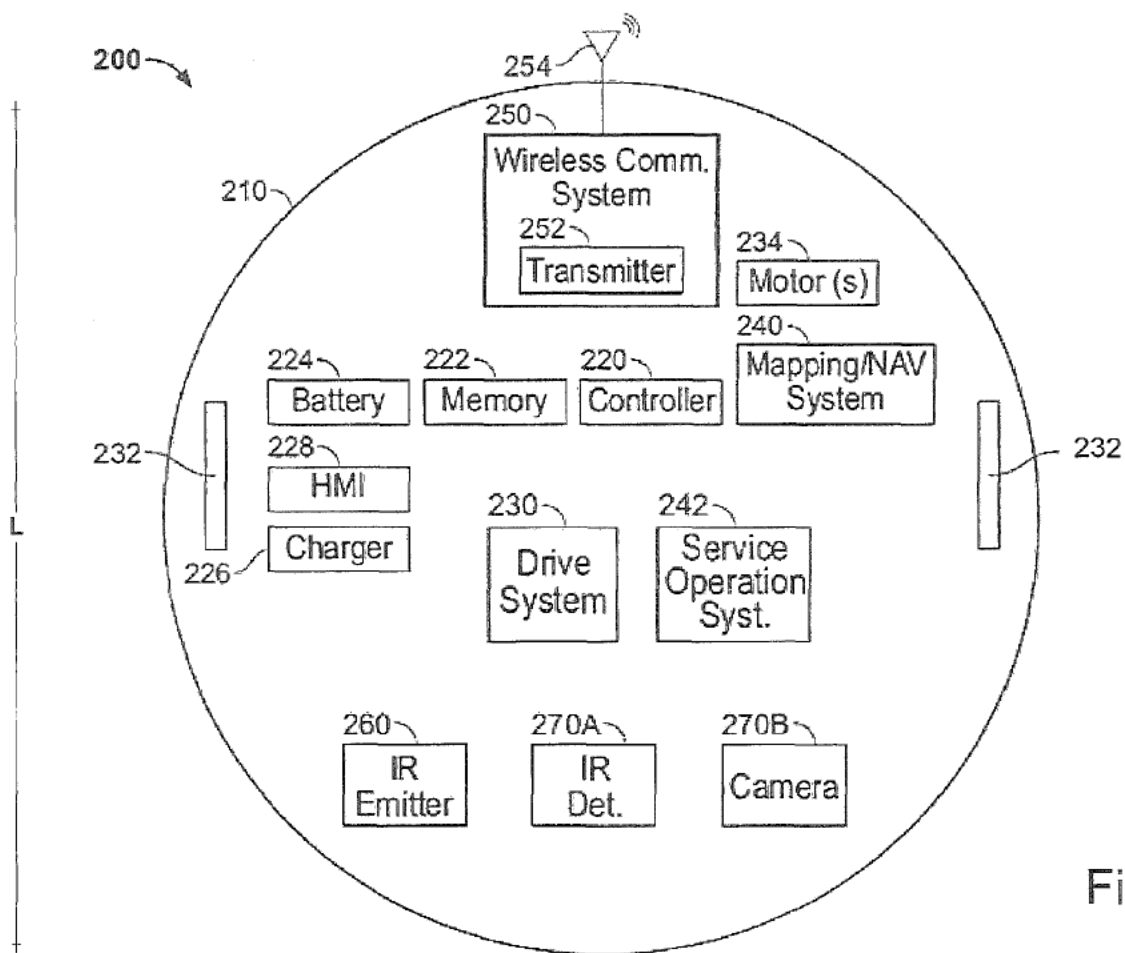


Fig. 3

Ex1006, Fig. 3.

410. It is also my opinion that it would have been obvious to combine the mapping and localization unit disclosed in Fong with the systems disclosed in Olson and Stachniss. Specifically, a POSITA would have known that including a computational unit for performing a robotic function, such as mapping and localization, was common practice. A POSITA would have had a reasonable expectation of success in adding this feature, as it would require no more than routine

addition of well-known technology, such as that disclosed in Fong, to the systems disclosed in Olson and Stachniss.

411. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong renders this limitation obvious.

c) Claim 13: The robot of claim 8, further comprising: a user interface for controlling the robot by at least one user.

412. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Fong or Stachniss in view of Fong discloses it.

413. For example, Fong discloses a human-machine interface, *i.e.*, a user interface. Fong explains:

The mobile robot **200** may be any suitable robot and it will be appreciated that not all of the components, features and functionality described herein are required in all embodiments of the invention. With reference to **FIG. 3**, the exemplary mobile robot 200 includes a chassis **210**, a controller **220**, memory **222**, a battery **224**, a battery charger **226**, **a human-machine interface (HMI) 228**, a drive system **230**, a mapping/navigation system **240**, a service operation system **242**, a wireless communication system 250, an IR emitter **260**, and pose sensors **270A-B**. The mobile robot **200** may be generally configured in the manner of or include features from the Roomba™ floor cleaning robot and/or robots as described in U.S. Pat. No. 7,024,278 and U.S. Published Application No. 2007/0250212, the disclosures of which are incorporated herein by reference, with suitable modifications.

Ex1006, 5:9–25; *see also* Ex1006, 5:26–36.

414. Fong depicts this user interface in Fig. 3, reproduced below.

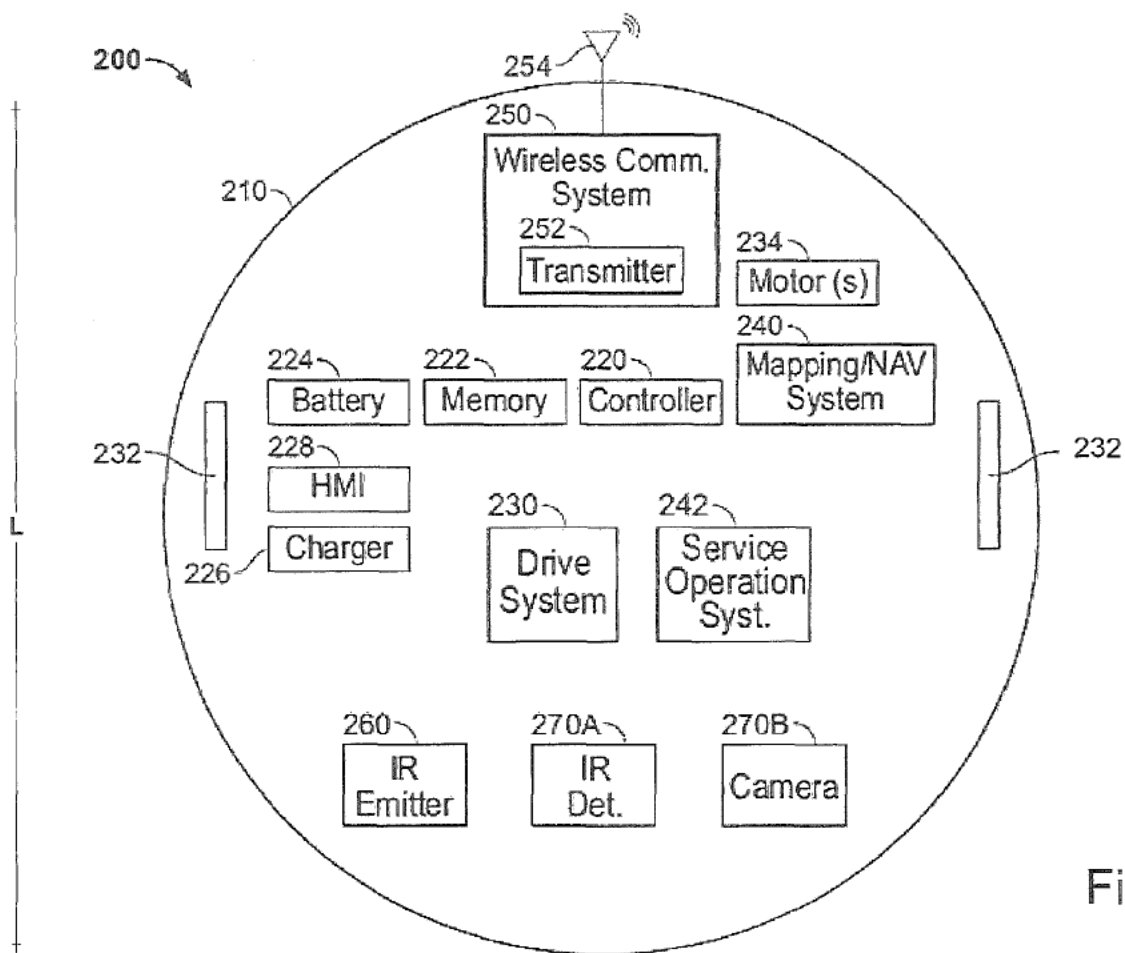


Fig. 3

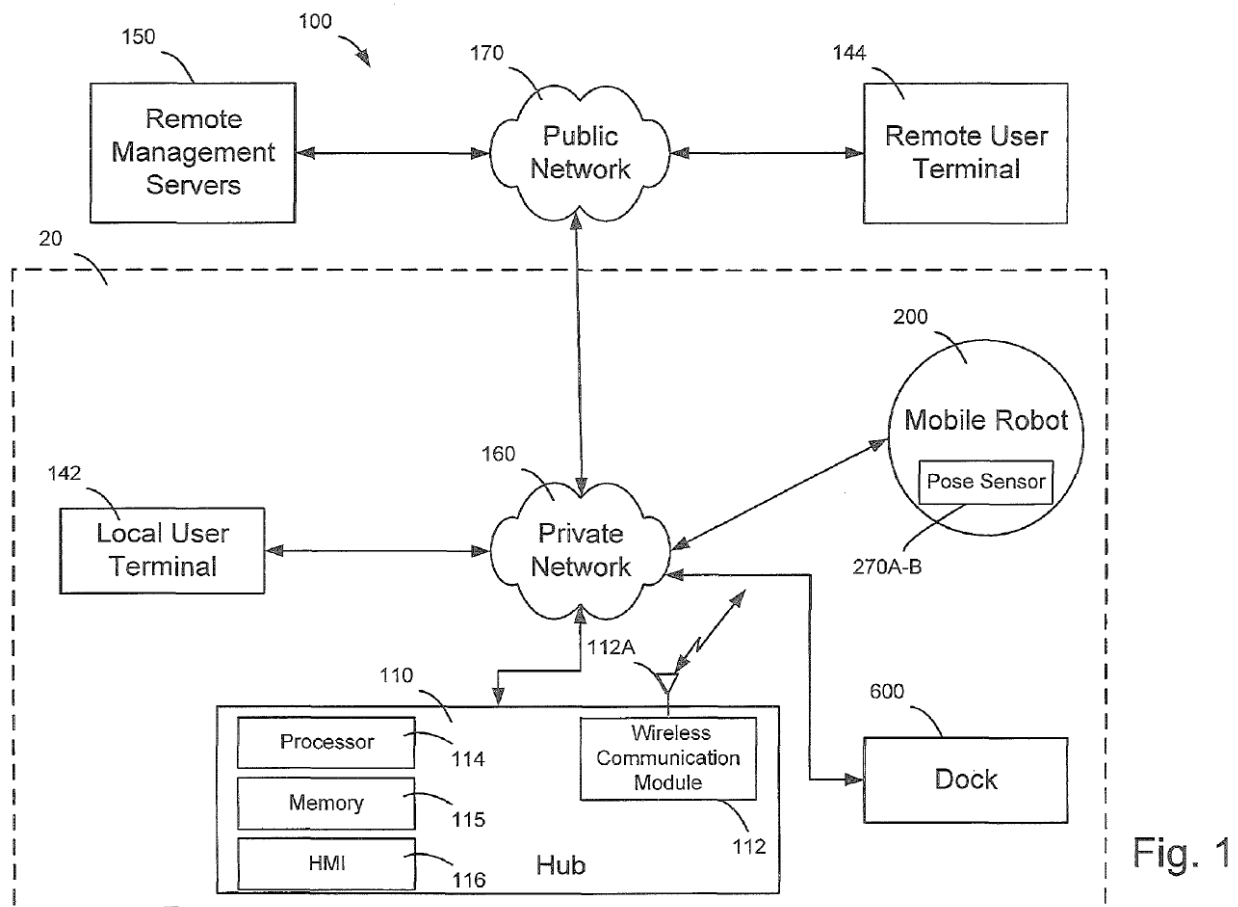
Ex1006, Fig. 3.

415. As a further example, Fong discloses a “local user terminal 142 and/or [a] remote user terminal 144.” Fong explains:

Although embodiments according to the invention are described with respect to the robotic management system **100**, it should be understood that other configurations fall within the scope of the invention. For example, the operations of the hub **110** and the dock **600** may be combined into a single unit. Moreover, the controller **220** is illustrated as part of the robot **200**; however, *some or all of the operations of the controller 220 may be performed by the dock 600 or by other processors, such as the remote management servers 150, 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.

416. By disclosing the operations of the controller 220 may be dedicated to local and remote user terminals, Fong discloses that its robot comprises a user interface. Fong further depicts these local and remote user terminals in Fig. 1, reproduced below. *See also* Ex1006, Fig. 4A.



Ex1006, Fig. 1.

417. A POSITA would have found it obvious to add the user interface of Fong to the systems disclosed in Olson/Stachniss. For example, a POSITA would have been motivated to include a means for providing user control, such as the one

disclosed by Fong to the systems of Olson/Stachniss given also the disclosures of Olson and Stachniss, which explain that user control may be beneficial under certain circumstances (*see supra* Section VII.A.1.n), and explain that passive SLAM systems are common (*see supra* Section VII.B.1.n), respectively. A POSITA would have had a reasonable expectation of success in making these combinations, as the POSITA would have known that local and remote control units were well-known and simple additions.

418. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong renders this limitation obvious.

d) 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:

419. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Fong or Stachniss in view of Fong discloses it.

420. Fong explicitly discloses a non-transitory computer-readable medium, including “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. Fong also explicitly states that these have computer readable instructions stored thereupon:

These computer program instructions may also be stored in a computer-readable memory that can direct a computer to other programmable data processing apparatus to function in a particular manner, such that the instructions stored in the computer readable memory produce an article of manufacture including instructions which implement the function/act specified in the block diagrams and/or flowchart block or blocks.

Ex1006, 2:35–42.

421. Fong explicitly discloses execution of the computer readable instructions by at least one processor:

The controller 220 may include any suitable configured processor (e.g., microprocessor) or processors. The controller 220 may be configured to control various components of the mobile robot 200. For example, the controller 220 may access and/or store information in the memory 222, control the data acquisition functions of the pose sensors 270A-B, provide instructions to the drive system 230, receive data and/or control a mapping function of the mapping/navigation system 240, communicate via the communication system 250 and/or HMI 228, monitor a charge of the battery 224 and the like.

Ex1006, 5:25–36.

422. It is also my opinion that it would have been obvious to a POSITA to combine Fong with Olson or Stachniss. Robots routinely have a memory to store and manage data, and a processor or microprocessor to carry out commands and make calculations and determinations. A POSITA would have known that a mobile autonomous robot contained a memory having computer readable instructions stored

within to be executed by a processor as it was standard practice for a robot to contain one.

423. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong renders this limitation obvious.

D. Grounds 5 and 6: Claims 1–18 are Obvious in View of Olson or Stachniss in combination with Schnittman

424. It is my opinion that to the extent that either Olson or Stachniss does not disclose claims 1–18, then it would have been obvious to combine those references with Schnittman to render each claim obvious.

1. Motivation to Combine Olson or Stachniss with Schnittman

425. A POSITA would have been motivated to combine Olson or Stachniss with Schnittman. Specifically, a POSITA would have been motivated to use the mapping algorithms disclosed in Olson or Stachniss in combination with ray-tracing steps to generate and update the map. Like each of Olson and Stachniss, Schnittman 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. Schnittman further explains that its method allows the map to be “update[ed]” by updating particle weights. Ex1007, 2:24–56. Stachniss explains that particle methods, like those disclosed in Schnittman, “allow[] for computationally efficient updates,” but “the number of necessary particles can grow very large.” Ex1005, 1166. In contrast, graph-based methods are “the method of choice for building large-scale maps,” but require

special handling when “revisit[ing] already mapped terrain.” Ex1005, 1165–66. Further, Schnittman explains that its method enables a robot to “navigate a scene **10** without colliding into obstacles **12** or falling down stairs” by “simultaneously localiz[ing] and map[ping] its surroundings using sensory inputs.” Ex1007, 9:3–21, 11:4–9. Consequently, a POSITA would have been motivated to combine a method of updating a local map using a particle-filter approach, as disclosed by Schnittman, in the context of a large graph-based map, as disclosed in each of Olson and Stachniss.

426. Furthermore, the references all state that it would be beneficial to combine the disclosed methods with others. For example, Olson explains that it should be combined with an autonomous robot, like the robot described in Schnittman. Ex1004, 9. Stachniss is a reference guide and was meant to be implemented by people in the robotics field. Ex1005, 1153. Schnittman explains that its method, like those in each of Olson and Stachniss, is a SLAM method, and is suitable for robots with sensors that rely on mapping and autonomous navigation. Ex1007, 1:14–36. Therefore, a POSITA would have had a reasonable expectation of success in combining either of Stachniss or Olson with Schnittman.

2. Element-by-element analysis

a) 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.**

427. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Schnittman or Stachniss in view of Schnittman discloses it.

428. Schnittman discloses this element. For example, Schnittman discloses updating a map (generating a map) based on executing a ray trace with scans generated by the sensor, the scans being associated with the plurality of nodes:

In some implementations, the method includes updating each particle's [plurality of nodes] pose, map, and weight. Updating the particle pose may include applying a robot motion model to the accumulated synchronized sensor data. The robot motion model models movement of the robot based on odometry and inertial measurements. Updating the particle map [plurality of nodes] may include ***executing a ray trace*** of the accumulated synchronized sensor data [scans being associated with the plurality of nodes] and applying a range sensor model to the accumulated synchronized sensor data. Updating the particle weight may be based on a number of measured ranges of the accumulated synchronized sensor data matching predicted ranges.

Ex1007, 2:24–34. *See also* Ex1007, 3:50–53, 5:1–6, 17:1–10, 22:42–45.

429. Schnittman further explains the manner in which a ray trace is performed:

Executing the ray trace may include, for each range measurement and bearing pair, receiving the bearing and an existing particle map, and computing a predicted range. 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. In some examples, applying the range sensor model includes only updating particle map cells corresponding to the synchronized sensor data.

Ex1007, 2:35–43. *See also* Ex1007, 3:56–64, 4:2–10

430. Schnittman further depicts ray tracing in a flow diagram of its mapping algorithm in FIG. 11, reproduced below.

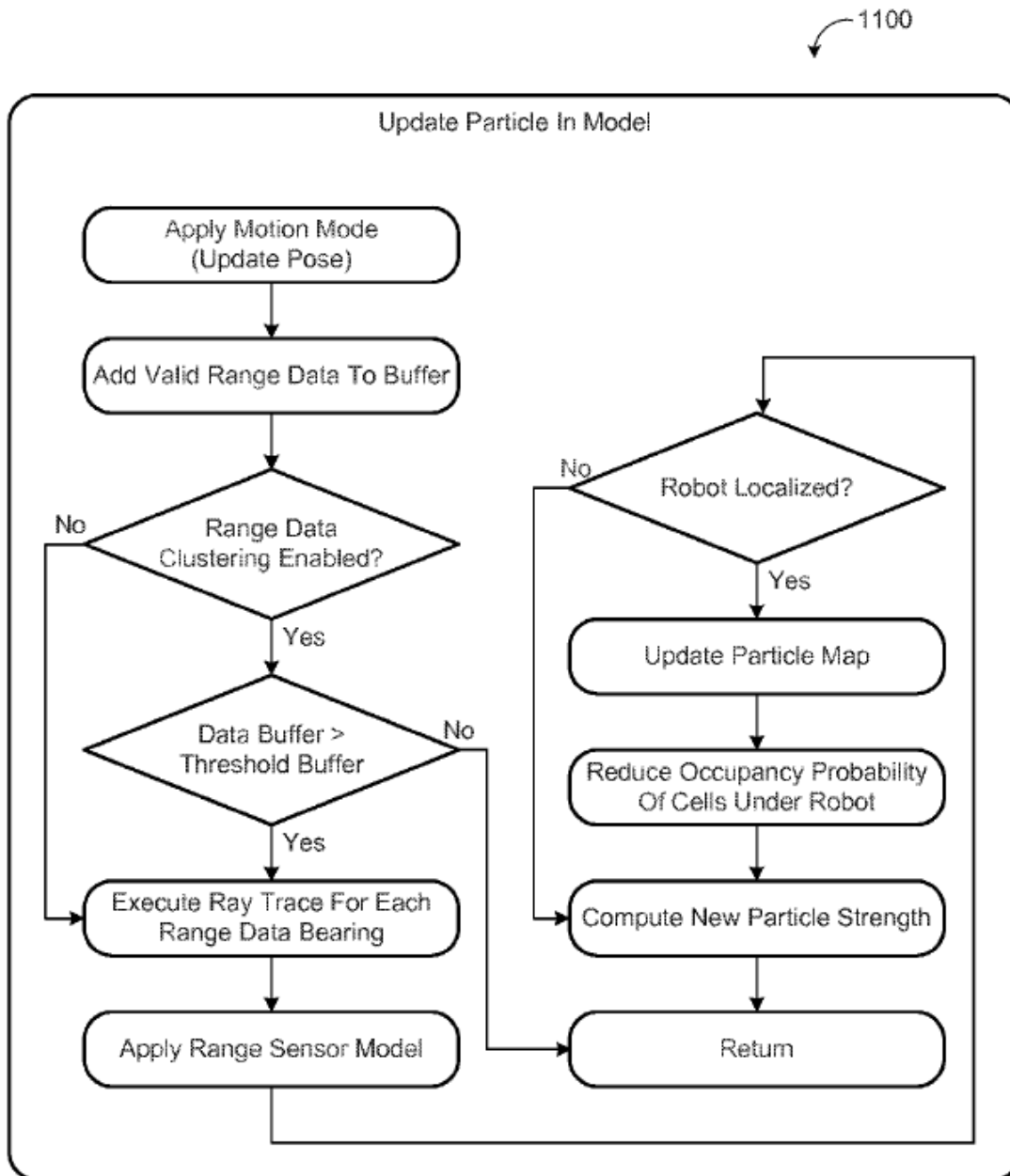


FIG. 11

Ex1007, FIG. 11.

431. It is also my opinion that it would have been obvious to a POSITA to combine the ray-tracing methods disclosed in Schnittman with the SLAM methods disclosed in each of Olson and Stachniss. A POSITA would have been motivated to make such a combination based on Schnittman's disclosure of a method to update a map in a dynamic environment, allowing, for example, the robot to localize itself and avoid obstacles. Ex1007, 9:3–21, 10:59–11:9. A POSITA would have had a reasonable expectation of success, as Schnittman explains that its method, like those in each of Olson and Stachniss, is a SLAM method using sensors and SLAM controllers. Ex1007, 1:14–15, 1:33–36, 5:54–59, 9:3–21, 10:59–11:3.

432. Therefore, it is my opinion that Olson in view of Schnittman or Stachniss in view of Schnittman renders this limitation obvious.

b) 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.

433. In my opinion, to the extent that either Olson or Stachniss does not anticipate this limitation, then Olson in view of Schnittman or Stachniss in view of Schnittman discloses it.

434. This limitation was addressed in the discussion of Element 2[d], and it is my opinion that Olson in view of Schnittman or Stachniss in view of Schnittman renders this limitation obvious for substantially the same reasons. *See* § VII.D.2.a.

VIII. SECONDARY CONSIDERATIONS

435. It is my understanding that, in parallel litigation, the Patent Owner has asserted that this patent, along with four other patents asserted, generally resolve a long-felt need, and that the technology claimed within the '325 patent enabled it to become an industry leader in autonomous robots and artificial intelligence. It identified a number of awards and recognition in the industry, and alleged that its products achieved commercial success and industry recognition given the number of robots it has sold and the hours of operation of those robots. It also alleged that the Petitioner has willfully infringed the asserted patents, and that the Petitioner's alleged infringement is a further indicator of non-obviousness. It is my further understanding that the Petitioner denies that it has infringed the asserted patents or copied the Patent Owner's technology.

436. It is my opinion that these vague allegations are not evidence of secondary considerations of non-obviousness tied to the Challenged Claims. For example, the Patent Owner did not establish any nexus between the claims and any of the alleged secondary indicia of non-obviousness. Moreover, it is my understanding that where there is a strong showing of obviousness, as here, even relevant secondary considerations supported by substantial evidence do not dislodge the primary conclusion of obviousness.

437. To the extent Patent Owner is permitted to provide any additional evidence or arguments supporting secondary considerations to rebut my opinions expressed herein, I reserve the right to respond by supplementing and/or amending this declaration or submitting a reply declaration to consider the alleged secondary considerations of nonobviousness.

IX. CONCLUSION

438. For the reasons set forth above, it is my opinion that the Challenged Claims of the '325 patent are invalid.

439. I hereby declare that all statements made herein of my own knowledge are true, and that all statements made on information and belief are believed to be true, and that these statements were made with knowledge that willful false statements and the like are so made punishable by fine or imprisonment, or both, under section 1001 of Title 18 of the United States Code, and that such willful false statements may jeopardize the Petition for *inter partes* review.

Executed on December 4, 2025
Scottsdale, Arizona

By: 

Dr. Lina J. Karam