

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. IPR2025-01603
U.S. Patent No. 10,823,576

**DECLARATION OF LINA J. KARAM, PH.D.
IN SUPPORT OF PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 10,823,576**

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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. 10,823,576 (“the ’576 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 1-36 (“the Challenged Claims”) of the ’576 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”).
- Prassler et al., Springer Handbook of Robotics, Chapter 65: Domestic Robots, (Bruno Siciliano and Oussama Khatib eds., Springer 2nd ed., 2016). (Ex1007, “Prassler”).

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. Shrotre, 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 '576 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 of 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 '576 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 '576 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 '576 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 '576 patent.

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

28. I understand that prior art to the '576 patent includes patents and printed publications in the relevant art that predate the priority date of the '576 patent. For the purposes of this Declaration, I am applying November 1, 2016, as the priority date of the '576 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 '576 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 '576 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 '576 PATENT

A. Summary of the '576 Patent

46. The '576 patent “relates generally to robotics, and more specifically to systems and methods for robotic mapping.” Ex1001, 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. Further, the patent discloses that “actions” are associated with poses, which may be nodes. Ex1001, 6:20-33, 16:20-28. The specification provides several examples of actions, including movements (e.g., turning) and functions, like cleaning. Ex1001, 6:20–33.

47. Each independent claim of the ’576 patent further requires that a range be associated with each node, where the range is based on a confidence measure related to the robot’s estimated position, (*i.e.*, pose). *See* Ex1001, 16:20-28 (“Each of nodes 602A-602D can be associated with a pose (e.g., including measurements such as (x, y, θ) of robot 202).”). Several of the dependent claims relate to that range, and further require that the range comprise, for example, a probability distribution or function.

48. Other dependent claims relate to loop closure, requiring that the robot recognize when it closes a loop (that is, when it returns to its starting position), and further requiring the robot limit uncertainty of the graph by constraining the graph based on that loop closure.

B. Summary of the Prosecution History of the '576 Patent

49. The '576 patent's application, U.S. Patent Application No. 16/356,160, was filed on March 18, 2019. Ex1001, 1. It claims priority to U.S. Patent Application No. 15/340,807, now U.S. Patent No. 10,274,325, filed November 1, 2016.

50. The Applicant amended its claims three times. First, the Applicant submitted a second preliminary amendment cancelling all originally-filed claims and adding three new independent claims and six claims depending on the first (i.e., the system claim) of the independent claims. Ex1002, 90–94.

51. Second, the Applicant amended its claims following a non-final rejection. Ex1002, 142–55. The Examiner found that all claims were either anticipated by U.S. Patent Publ. No. 2017/0102709 A1 (“Kwak”) or obvious in view of Kwak in combination with U.S. Patent Publ. No. 2012/0219207 A1 (“Shin”). Ex1002, 103–11. The Examiner explained that Kwak disclosed all elements of the independent claims and four of the dependent claims, and that Kwak in view of Shin disclosed the remaining two dependent claims. Ex1002, 106–10. In response, the Applicant added the following to each of the independent claims, “the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based

on confidence measure at a respective node.” Ex1002, 142–55. As discussed more fully below, this amendment only recites features that were well-known in the robotic mapping art, particularly in SLAM-related publications.

52. The Applicant also added five new claims depending on the first independent claim and applied each of the eleven dependent claims (new and old) to each of the three independent claims, for a total of 36 claims. Ex1002, 142–55.

53. In response, the Examiner indicated that claims 21–40 and 46–56 would be allowed, but that 41–45 were rejected due to a lack of antecedent basis for “the system,” where those claims depended from claim 28, which recited “a method.” Ex1002, 158–62. The Applicant responded with a third amendment, changing those claims to “the method of claim 28.” Ex1002, 218–30.

54. With that amendment, the Examiner then issued a Notice of Allowance on June 29, 2020. Ex1002, 231–35.

C. Overview of the Challenged Claims

55. There are three independent claims in the ’576 patent: claims 1, 13, and 25. Claim 1 is a system claim, claim 13 is a method claim, and claim 25 is an apparatus claim.

56. I understand that Petitioners are challenging all of the claims in the ’576 patent (the “Challenged Claims”). I have analyzed each of these claims.

No.	Limitation
1[pre]	A system for traveling a robot along a route, comprising:
1[a]	a memory having computer readable instructions stored thereon; and
1[b]	at least one processing device configurable to execute the computer readable instructions to,
1[b][1]	collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment,
1[b][2]	generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and
1[b][3]	associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.
2	The system of claim 1, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.
3	The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.
4	The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.

No.	Limitation
5	The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, determine the robot returned to a start position based on detecting a home locator in the environment.
6	The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.
7	The system of claim 6, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which corresponds to surrounding region around each node of the plurality of nodes.
8	The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.
9	The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.
10	The system of claim 1, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.
11	The system of claim 1, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.
12	The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.
13[pre]	A method for traveling a robot along a route, comprising:

No.	Limitation
13[a]	collecting data by at least one sensor coupled to the robot as the robot travels along the route in an environment;
13[b]	generating a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node; and
13[c]	associating actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.
14	The method of claim 13, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.
15	The method of claim 13, further comprising: estimating distance traveled by the robot along the route based on revolution of wheels on the robot.
16	The method of claim 13, further comprising: estimating distance traveled by the robot along the route based on sequential images captured by the at least one sensor.
17	The method of claim 13, further comprising: determining the robot returned to a start position based on detecting a home locator in the environment.
18	The method of claim 13, further comprising: limiting uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.

No.	Limitation
19	The method of claim 18, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.
20	The method of claim 13, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.
21	The method of claim 13, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.
22	The method of claim 13, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.
23	The method of claim 13, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.
24	The method of claim 13, further comprising: actuating one or more systems selectively as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.
25[pre]	A non-transitory computer readable medium comprising computer readable instructions stored thereon that when executed by at least one processing device configure the at least one processing device to,
25[a]	collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment;

No.	Limitation
25[b]	generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node; and
25[c]	associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.
26	The non-transitory computer readable medium of claim 25, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.
27	The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.
28	The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.
29	The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, determine the robot has returned to a start position based on detecting a home locator in the environment.

No.	Limitation
30	The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.
31	The non-transitory computer readable medium of claim 30, wherein each node of the plurality of nodes include an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.
32	The non-transitory computer readable medium of claim 25, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.
33	The non-transitory computer readable medium of claim 25, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.
34	The non-transitory computer readable medium of claim 25, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.
35	The non-transitory computer readable medium of claim 25, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.
36	The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.

57. 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

58. 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.

59. 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

60. 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</i> ,	Jan. 31, 2016	1005

<i>Chapter 46: Simultaneous Localization and Mapping</i> , Springer (2 nd ed.) (“Stachniss”)		
U.S. Patent No. 9,538,892 (“Fong”)	Oct. 5, 2012	1006
Prassler et al., <i>Springer Handbook of Robotics</i> , Chapter 65: Domestic Robots, Springer (2 nd ed.) (“Prassler”)	Jan. 31, 2016	1007

61. 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.

62. 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).

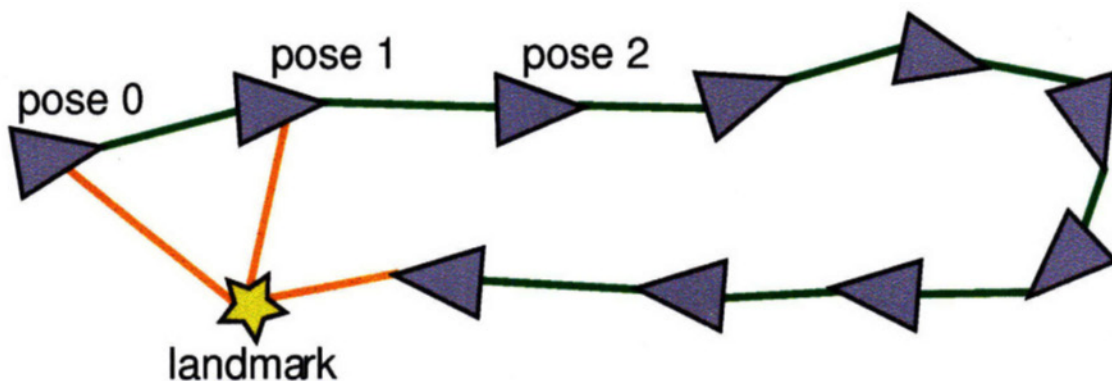
B. General Overview of the Primary Prior Art References

63. The following sections provide a brief description of the prior art systems and software that invalidate the '576 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 Prassler disclose or suggest the features of the Challenged Claims.

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

64. “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.

65. 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.

66. 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.

67. 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, 100-103, Figure 5-4.

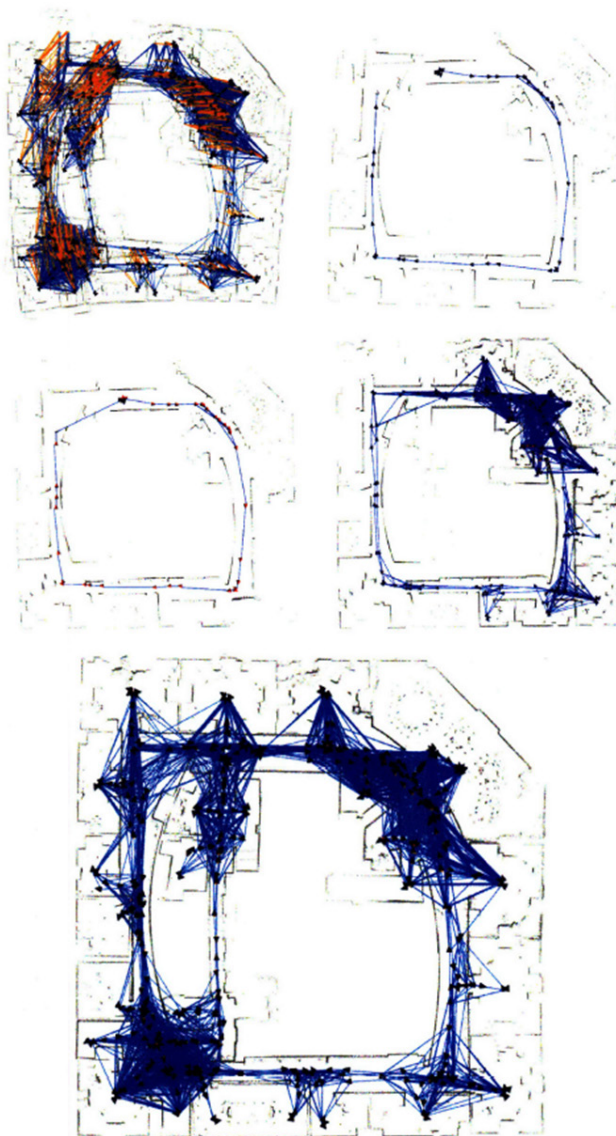


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

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

68. “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.

69. 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.

70. 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.

71. 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.

72. 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).

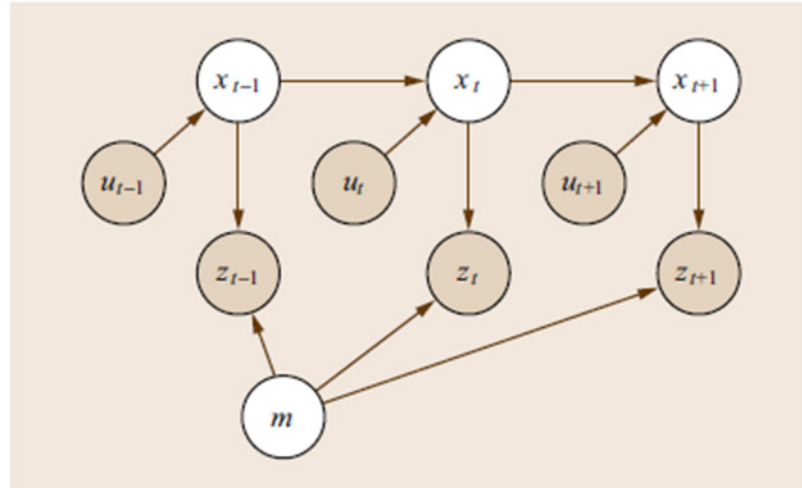


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

73. 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.

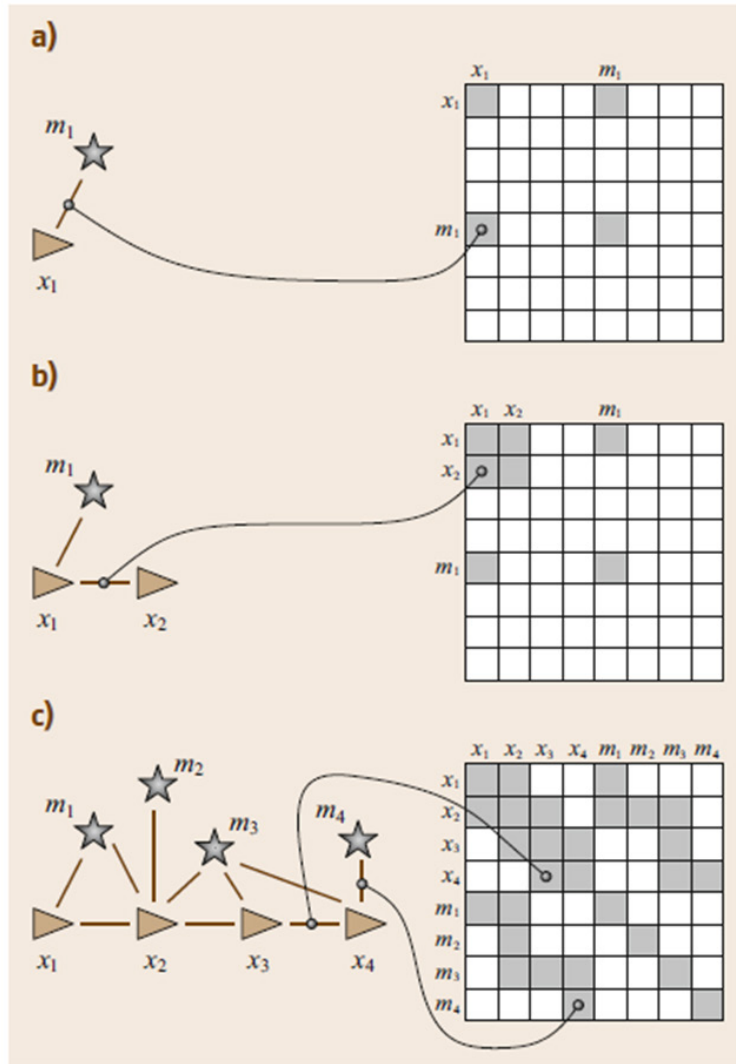
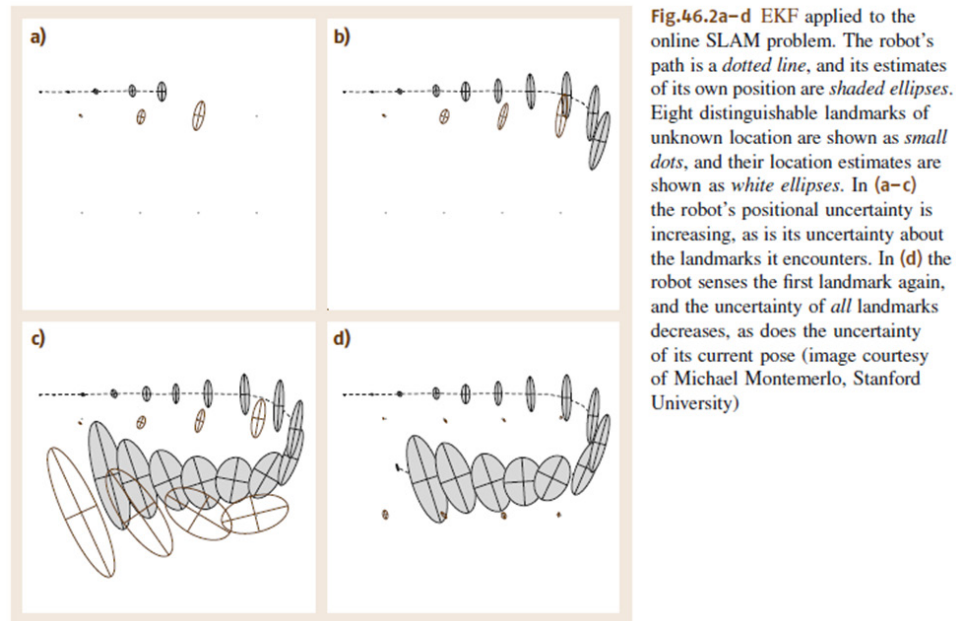


Fig.46.7a-c Illustration of the graph construction. The (a) diagram shows the graph, the (b) the constraints in matrix form. (a) Observation is landmark m_1 . (b) Robot motion from x_1 to x_2 . (c) Several steps later

Ex1005, Fig. 46.7a-c.

74. 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”)

75. 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.

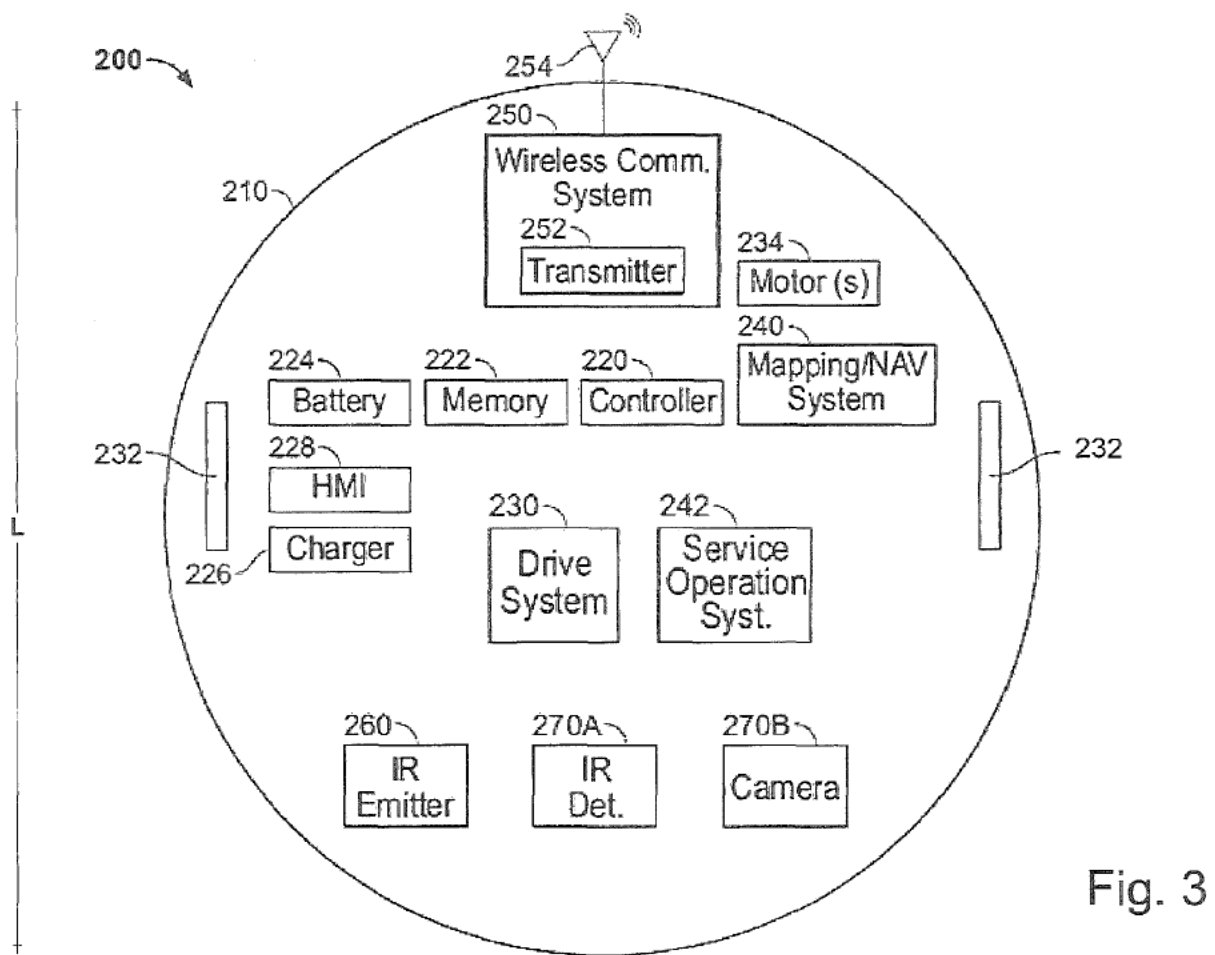


Fig. 3

Ex1006, Fig. 3.

4. “Springer Handbook of Robotics (2nd ed.) Chapter 65: Domestic Robots” (“Prassler”)

76. Prassler is Chapter 65 of the “Springer Handbook of Robotics,” discussed in Section VI.B.2 with respect to Stachniss. *See* § VI.B.2; *see also*

Ex1008, ¶ 33. It is in a larger section called “Robots at Work,” which describes practical applications of robotic technology.

77. Prassler documented the development of robots to assist with household (“domestic”) tasks, beginning with household floor cleaners. Ex1007, 1729. Prassler explains that, as practitioners developed robots to assist with domestic tasks, “everybody expected cleaning to be the killer app for domestic robots.” Ex1007, 1729. Prassler divides the history of floor cleaners into three “generations.” Ex1007, 1730–37. The first generation consisted of proof of concept devices, prototypes, and expensive consumer products, that included high-end sensors and/or a large number of sensors and aimed at sophisticated robotics capabilities. Ex1007, 1730–32. As Prassler explains, “[t]he first mention of a domestic cleaning robot dates back to 1985. The device, nicknamed *Robby*, was developed by Hitachi starting in 1983 Very similar to today’s cleaning robots . . . , Robby already mapped its environment and used the map for path planning.” Ex1007, 1730. But most products developed in that era were too expensive to release. For example, Prassler explains that Dyson announced the DC06 autonomous cleaner, with “three onboard CPUs, more than 50 sensors for obstacle avoidance, cliff-detection, localization and more,” an “announced list price of approximately US\$ 4,000,” but the “DC06 never made it to the market.” Ex1007, 1730–31.

78. Prassler's second generation of robots consisted of cheaper devices with less-complicated robotics features. Ex1007, 1731–33. The Roomba, released in 2002, was seen as “breakthrough in domestic cleaning robotics” on account of its low price, even though the first Roombas could not ensure complete or efficient coverage because they lacked capacity to build maps. Ex1007, 1732. As Prassler explained, “[s]ystematic coverage, however, is impossible without absolute positioning and without decent knowledge of the environment.” Ex1007, 1732. Roomba's approach was to use “smart heuristics” involving a “combination of random motion and hardcoded area-covering motion patterns to achieve a certain level of coverage.” Ex1007, 1732.

79. Prassler's third generation of robots took advantage of decreasing electronics prices to introduce advanced sensors and computing that had previously been reserved for high-cost machines, into the low-cost paradigm of second generation robots to achieve systematic or near-systematic coverage at a low cost. Ex1007, 1733–37. Prassler explains that the designers of this generation of robots needed to target “[c]ustomers who care about the price and quality” by providing “a low-cost navigation system based on low-cost sensors” that can accomplish systematic or near-systematic coverage with “automatic charging stations.” Ex1007, 1734. Various manufacturers developed and provided such a system by using SLAM methods incorporating visual odometry or with laser rangefinders.

Ex1007, 1735-6, 1749–54. “The true achievement of the developers of the above systems [Table 65.2 (reproduced below)], which cannot be assessed high enough, is that they managed to reduce the cost of these technologies and at the same time make them robust enough for 24/7 operation.” Ex1007, 1736.

Table 65.2 Systematic cleaning at low-cost. The information in this table was partly collected from the websites and the technical documentation of the manufactures and partly from public websites such as www.botroom.com, staubsaugerroboter-test.org, www.robotreviews.com, www.geek.com, gizmodo.com, www.engadget.com

					
Manufacturer	LG	Samsung	Neato Robotics	Iclebo	Evolution Robotics/iRobot
Distributor			Vorwerk	Philips	Dirt Devil EVO/iRobot
Model	Hom-Bot 3.0	Navibot SR 8895 Silencio	Neato XV-21	Philips FC9910/01 HomeRun/ iclebo smart	Mint 4200
CPU	32 bit	2 CPUs			ARM7
Drive	Differential	Differential	Differential	Differential	Differential
Sensors	Camera (ceiling), camera (floor), sonar & infrared for collision avoidance cliff sensors, gyroscope, acceleration	Range sensors camera, cliff sensors, collision sensors, gyro	1-D laser range finder, cliff sensor, gyroscope, acceleration,	Camera (ceiling), cliff sensor, infrared for collision detection, gyroscope,	Northstar Indoor GPS, cliff sensors, bumper, gyro
Mapping and localization	SLAM	SLAM based on ceiling pictures at 30 fps (Visionary Mapping System)	SLAM based on laser range finder (onboard Room Positioning System (RPS))	SLAM based on ceiling pictures	SLAM with North- star, map-building
Navigation/coverage	Systematic	Systematic	Systematic	Systematic	Systematic
Cleaning technology	Brush roller, 2 side brushes	Brush roller, 2 side brushes	Bristled brush	Brush roller, 2 side brushes, micro-fiber mop	Dry or wet (or pre- moistened) microfiber cloths
Run time (min)	75	90	90	70	180
Performance	–	80 m ² /h	–	40 m ² /h	–
Docking/recharging station	Yes	Yes	Yes	Yes	No
Size (Ø/h) (cm)/(cm)	36/9	35/8	34× 34/10	35/10	31× 11/ 29
Weight (kg)	3,2	3,2	5	4	2
Year of launch	2011	2011	2012	2011	2010
Price range	US\$ 799.00 (Amazon.com)	EUR 349.00 (Amazon.de)	US\$ 350.00 (Amazon.com)	EUR 499.00 (Amazon.de)	US\$ 174.00 (Amazon.com)

Ex1007, Table 65.2.

VII. ANALYSIS OF THE CHALLENGED CLAIMS AGAINST THE PRIOR ART

80. 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.

81. It is my understanding that each of the prior art references analyzed in this declaration meets the legal requirements for prior art to the '576 patent. I have performed my analysis with this understanding.

82. Based upon my analysis, it is my opinion that the Challenged Claims of the '567 patent are anticipated or rendered obvious by the following prior art grounds:

Ground	Claims	Basis for Rejection
1	1—36	Anticipation by Olson
2	1–11, 13–23, 25–36	Anticipation by Stachniss
3	1–36	Obviousness over Olson in combination with Fong
4	1–36	Obviousness over Stachniss in combination with Fong
5	1–36	Obviousness over Stachniss in combination with Prassler

83. 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—36 are Anticipated by Olson

84. In my opinion, claims 1–36 of the '576 patent are anticipated by Olson. Further, claims 1–36 are rendered obvious by Olson.

1. Element-by-Element Analysis

a) Element 1[pre]: A system for traveling a robot along a route, comprising:

85. To the extent that the preamble is limiting, it is my opinion that Olson discloses it. Olson discloses a system for traveling a robot along a route. Ex1004, 3, 8-17,

86. Olson discloses a robot that moves through an environment while simultaneously mapping the environment. Ex1004, 3, 8-12, 43–49, 97, 105-106, 109, 113-114. This is the same as the '576 patent, which describes a robot that can be operated to or can autonomously move along a desired route. Ex1001, 6:8–19. 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. 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 system 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.

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

b) Element 1[a]: a memory having computer readable instructions stored thereon; and

88. It is my opinion that Olson discloses this limitation. Olson discusses the robot’s memory and the impact the 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.

89. In addition, Olson discusses “memory usage of the algorithm,” “runtime” and “CPU requirements.” Ex1004, 98. A POSITA would understand 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.

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

c) Element 1[b]: at least one processing device configurable to execute the computer readable instructions to,

91. It is my opinion that Olson discloses this limitation. Olson explicitly discusses the use of a processing device when it discusses a CPU (“central processing unit”). Specifically, Olson talks about different CPU time to generate a map and implement the algorithms. Ex1004, 46, 49, 75-77, 94-95, 98-99. Olson also discusses optimizing CPU time. Ex1004, 94. Olson further discloses processing and corresponding hardware. Ex1004, 119, 122. Further, a POSITA would understand that Olson’s disclosure of a processor that executes algorithms also discloses that the processor executes computer readable instructions. Ex1004, 49.

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

- d) **Element 1[b][1]: collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment,**

93. It is my opinion that Olson discloses this limitation. Olson explicitly discloses collecting data by at least one sensor as it travels along a route. Ex1004, 11–12, 109, 113-114, Figures A-1, A-5.



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.

In the common case, sensors are mounted on the robot. 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 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.

Ex1004, 12.

94. These sensors include cameras, laser scanners/lidars, radars, inertial measurement unit, and global positioning systems. Ex1004, 14, 16, 23, 32, 34, 109, 113.

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

- e) **Element 1[b][2]: generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data**

as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and

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

97. As discussed in Sections VII.A.1.a–d *supra*, 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. *See* §§ VII.A.1.a–d. The robot collects sensor measurements regarding the robot’s position called poses (represented by nodes in a graph) and those poses (nodes) are connected by edges (constraints). 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. A POSITA would understand that a sequence of poses would represent a route, and thus the generated map would include information about the robot’s location and position in the environment along the robot’s traveled route.

98. 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.

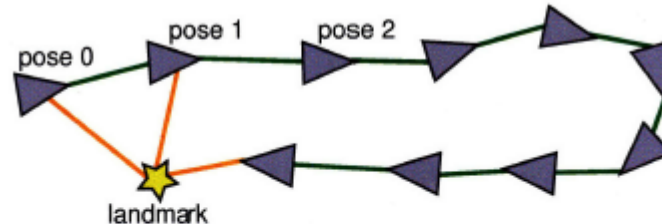


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

99. Olson further discloses that the map is generated by taking measurements at a plurality of poses, which may be collected into a pose graph wherein the poses are represented as nodes in the graph. In addition, 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.

100. 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.

101. 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.”).

102. 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, 53, Figure 3-17.

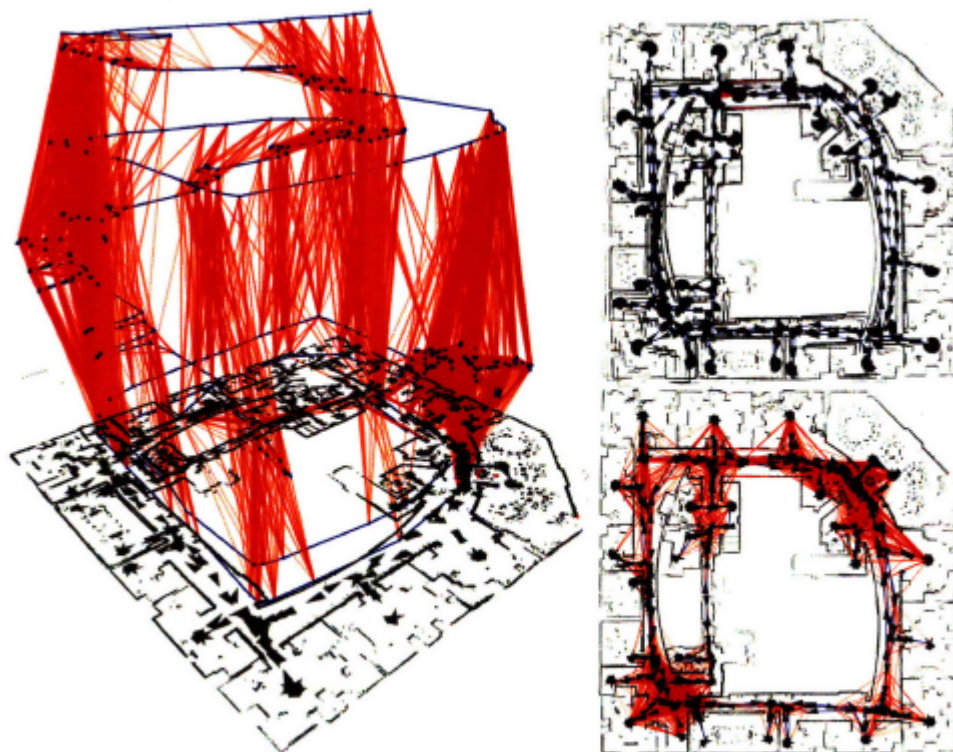


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

103. 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.

104. This map is generated as the robot travels along the route. For example, Olson explains that the method may be “used in online settings—i.e., where the

optimization problem [map] is constantly changing as new sensor data continuously arrives.” Ex1004, 11–12; *see also* Ex1004, 89–103.

105. Further, Olson discloses that each of the nodes 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 (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”).

106. Olson further indicates that “the goal is to estimate the positions of all the nodes (the state variables).” 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.

107. A POSITA would consider these to disclose computing ranges as taught by the '576 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, 16:32–48.

f) Element 1[b][3]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

108. In my opinion Olson discloses this limitation.

109. As discussed in Section VII.A.1.d *supra* (Element 1[b][1]), Olson's Pose/Feature graph contains poses that represent actions undertaken by the robot. *See* § VII.A.1.d. Olson discloses that a robot's actions include, for example, "avoiding obstacles, planning routes to some goal, or [] trying to map an environment." Ex1004, 55; *see also* Ex1004, 9, 89, 105. Part of the way the robot accomplishes this is via the use of sensor data, such as odometers, LIDAR, and cameras, and associating that data with a position on a map. Ex1004, 15, 48, 109, 113-114, 122. A POSITA would consider the measurements of the robot's movements, location and position, to be representative of the actions undertaken by the robot. Ex1004, 43–49, 109–113. Olson explains that information is gathered to develop the edges between the nodes. Ex1004, 15. For example, Fig. 1-4, below, shows the odometry data between the nodes, landmarks and poses. Ex1004, 15.

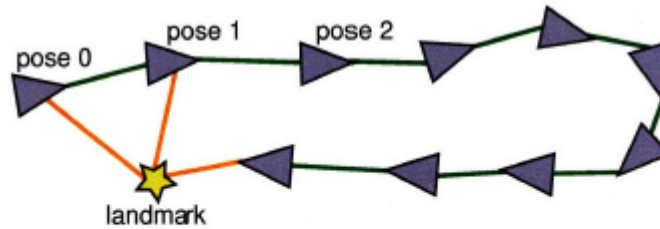


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

- g) Claim 2: The system of claim 1, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.**

110. In my opinion, Olson discloses this limitation.

111. Olson discloses a method for a robot to create a two-dimensional pose graph of an environment. Ex1004, 15–16. Specifically, Olson states that it is directed to “two-dimensional pose graphs and rigid-body constraints due to their ubiquity and applicability to many terrestrial mapping systems.” Ex1004, 19; *see also* Ex1004, 61 (“We also limit ourselves to 2D, though our methods also apply in principle to 3D.”). The map can depict the orientation and position of the robot and obstacles (landmarks) in the environment. Ex1004, 13, 15. This is demonstrated in Figure 1-4, reproduced below. The triangles represent the orientation and position of the robot, while the star represents the landmark. Ex1004, 15.

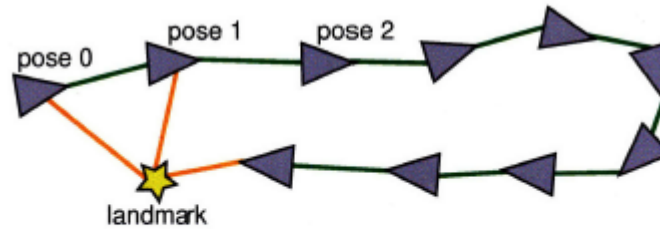


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

112. To create a map, the robot moves throughout the environment, and gathers information. Ex1004, 15. Olson explains that “[w]hen a robot obtains new information about the environment, this information must be rapidly incorporated into the model of the world so that the robot’s obstacle avoidance and path planning activities can take that information into account.” Ex1004, 89.

113. Olson provides an example of a map when it discloses the map of the Intel Research Center (IRC), which a robot generated. Ex1004, Figure 3-17 (reproduced below), 49, 53, 83–84, 100–03.

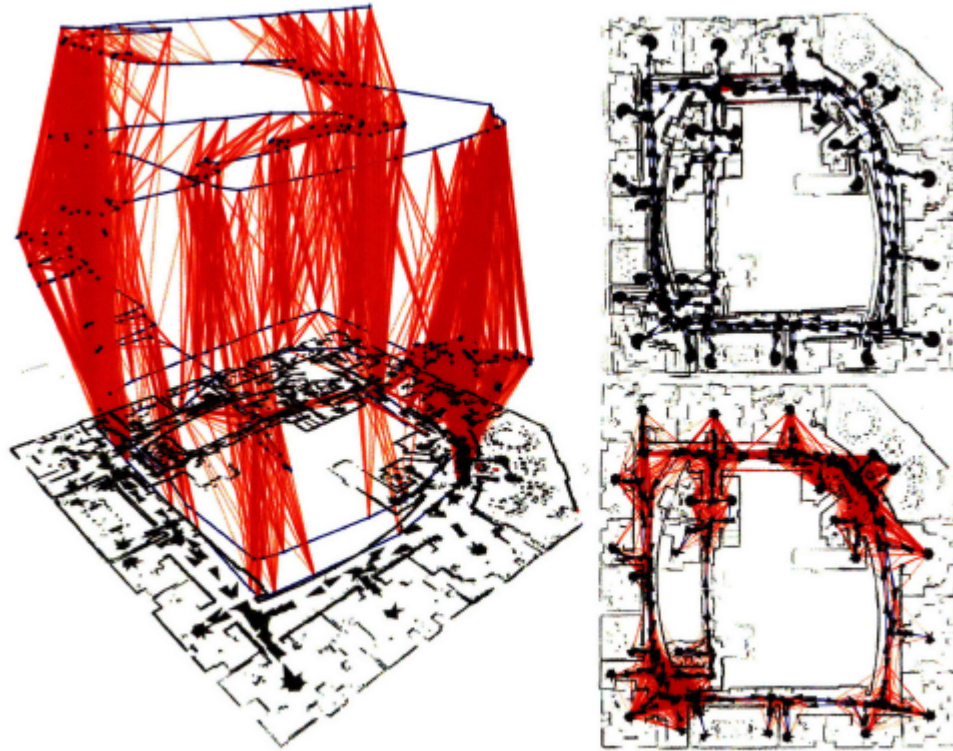


Figure 3-17: Intel research center. Left: the pose graph resulting from our algorithm. Top right: the uncorrected map. Bottom right: the optimized map, viewed from above.

Ex1004, Figure 3-17.

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

- h) Claim 3: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.**

115. In my opinion, Olson discloses this limitation.

116. Olson explicitly discloses that the robot's inputs can include wheel odometry, which are measurements taken by the robot's wheels. Ex1004, 48, 52,

114. The robot is able to use this information to estimate the distance traveled.

Ex1004, 60–63.

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

- i) **Claim 4: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.**

118. In my opinion, Olson discloses this limitation.

119. Olson discloses that distance can be estimated from sequential images that are captured by a camera (sensor). Ex1004, 15–16, 60–63. These images are then used to create a map of an environment. Ex1004, 15. Figure 1-3, reproduced below, is an example of a map created by sequential images captured by a camera. Ex1004, 14.

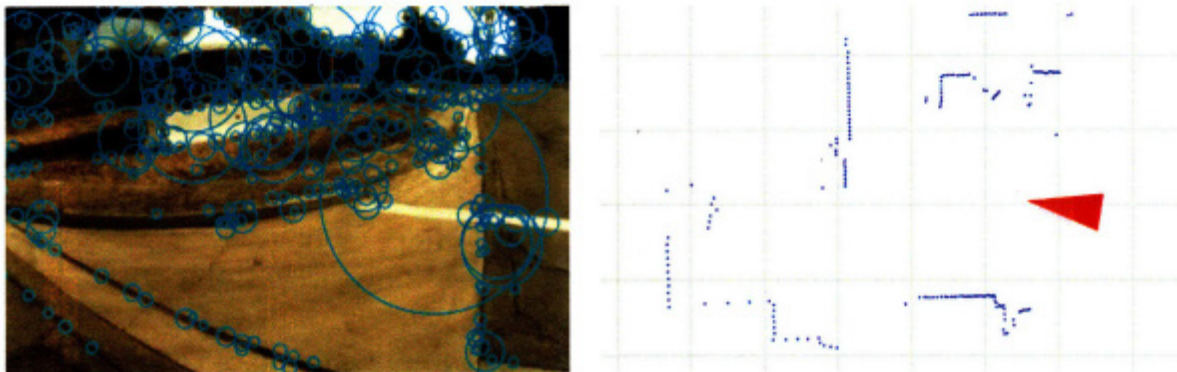


Figure 1-3: Sample sensor data. Different sensor modalities present different challenges when trying to “close the loop”. Left: Camera-derived visual features can be richly descriptive, but are also cluttered and not consistently repeatable under changing lighting and viewpoint. Right: Laser-scan data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

Ex1004, Figure 1-3.

120. In order to determine distance from images, Olson discloses the use of extraction algorithms, such as SIFT and RANSAC, to find the most likely rigid-body

transformation, which also provides an estimation of the robot's motion including the distance traveled and the direction of travel. Ex1004, 109–113.

Each putative rigid-body transformation is scored by counting the number of features B_i that, when projected, lie near the counterpart A_i . We used a distance threshold of 1 m in our implementation. The rigid-body transformation with the largest score is output as a candidate loop closure hypothesis, which can be filtered...

Ex1004, 113.

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

j) **Claim 5: The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, determine the robot returned to a start position based on detecting a home locator in the environment.**

122. In my opinion, Olson discloses this limitation.

123. Olson discloses that loop closure. 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.

124. 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.

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

k) Claim 6: The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.

126. In my opinion. Olson discloses this limitation.

127. As explained in Section VII.A.1.j *supra* (Claim 5), Olson discloses a system that implements “loop closing.” See § VII.A.1.j.

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

128. 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.

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 with the ending position. Ex1004, 60.

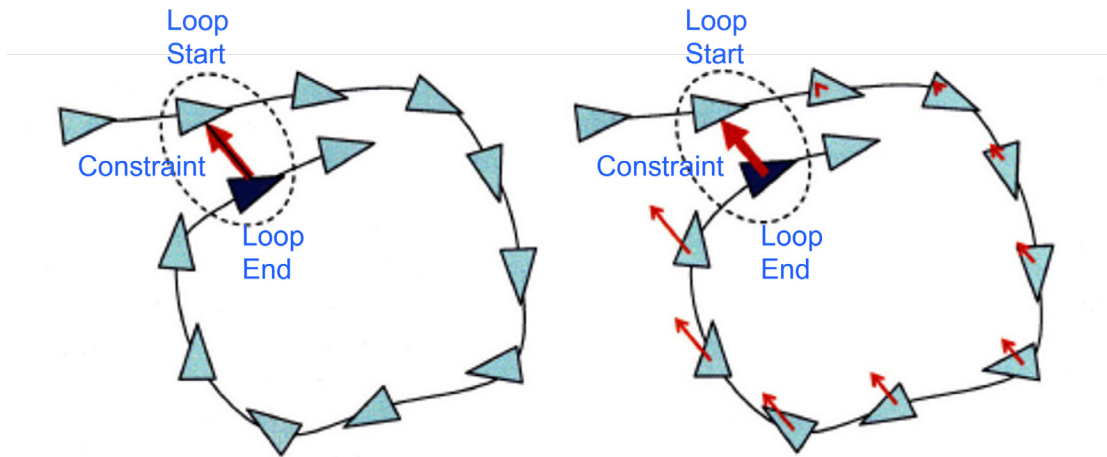


Figure 4-1: Map Optimization Intuition. The χ^2 error of a graph with a poorly-satisfied constraint (left, red arrow) can be reduced by distributing small adjustments around the nodes in the loop (right).

Ex1004, Figure 4-1 (annotated).

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

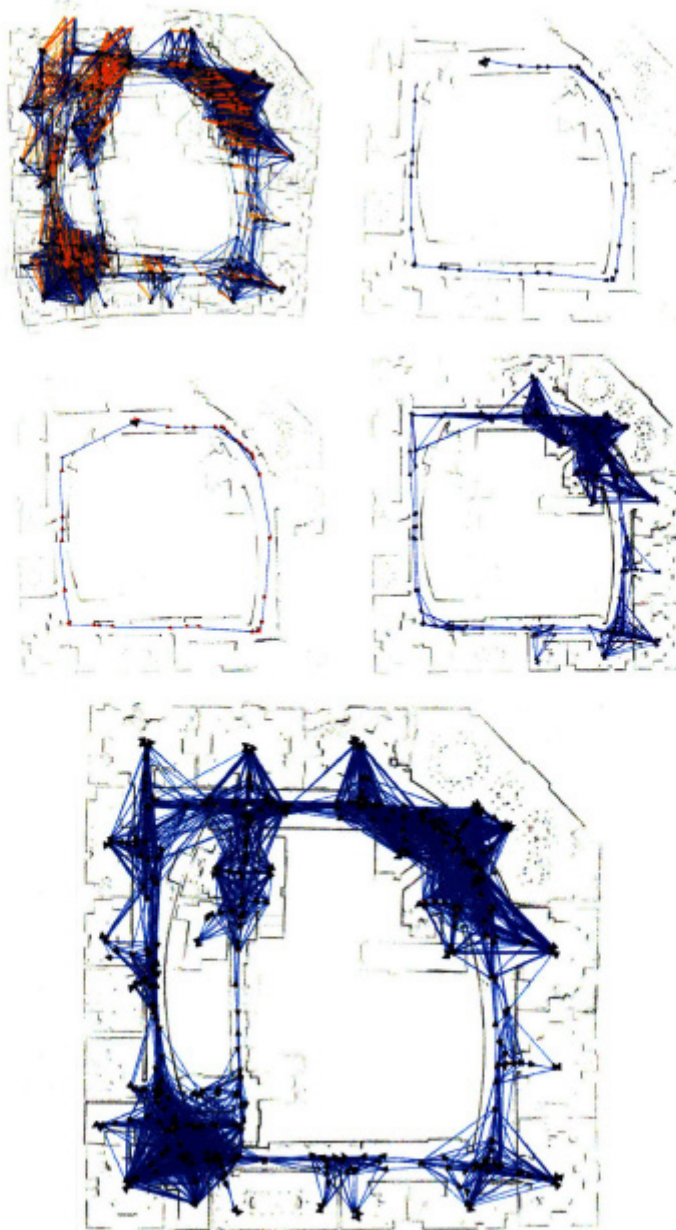


Figure 5-4: Intel Research Center. Top-left: open loop trajectory; top-right: just before closing the first loop, middle-left: just after closing the first loop; middle-right: about half way through the data set; bottom: the posterior map.

Ex1004, Figure 5-4.

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

- I) Claim 7: The system of claim 6, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which corresponds to**

surrounding region around each node of the plurality of nodes.

131. In my opinion, Olson discloses this limitation.

132. As explained in Section VII.A.1.e *supra* (Element 1[b][2]), Olson discloses that each node in its pose/feature graph is a random variable and has an associated probabilistic 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”); *see also* § VII.A.1.e.

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

m) Claim 8: The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.

134. In my opinion, Olson discloses this limitation.

135. As explained in Sections VII.A.1.e, 1 *supra* (Element 1[b][2] and Claim 7), Olson discloses a probabilistic distribution for each node, representing the uncertainty and thus the confidence measure. Specifically, Olson discloses that each

node corresponds to a random variable and has an associated probabilistic distribution. Ex1004, 12-13, 19–20; *see also* §§ VII.A.1.e, 1.

136. 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 (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 .”), 66 (disclosing covariance matrix of probabilistic distribution “estimates the relative confidence of

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

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

n) **Claim 9: The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.**

138. In my opinion, Olson discloses this limitation.

139. As explained in Section VII.A.1.e *supra* (Element 1[b][2]), 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.

140. 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 Figures 1-4 and 2-2, reproduced below, where each pose is given a position relative to the starting location (pose 0).

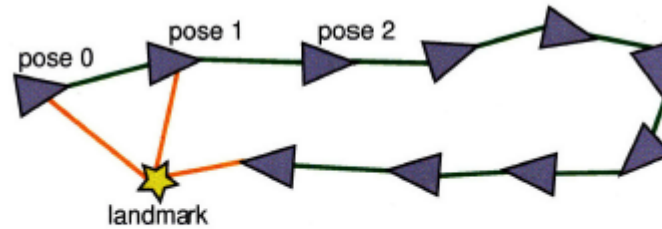


Figure 1-4: A Simple Pose/Feature graph. The robot's trajectory is discretized into a series of poses (triangles). These poses, as well as landmarks (stars), are nodes in the pose graph. Edges in the pose graph represent constraints between the positions of nodes, such as those derived from odometry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

Ex1004, Figure 1-4.

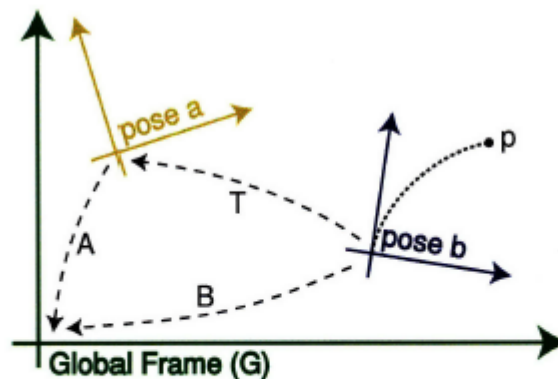


Figure 2-2: Coordinate transformations. Each robot pose represents a local coordinate system which can be related to the global coordinate by a rigid-body transform. Two local coordinate systems can also be related, e.g., $B = AT$. Point p , expressed with respect to coordinate frame B , can be projected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

Ex1004, Figure 2-2.

141. Further, landmarks (features or obstacles) are also noted by the robot and given a position relative to the nodes and starting location. Ex1004, 15.

142. 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, 62–63. This is further represented below.

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

Figure 4-2: State Space Representations. The commonly used state space $\mathbf{x}_{\text{global}}$, the rigid-body transformation state space $\mathbf{x}_{\text{rel}}$, and our proposed “global incremental” state space $\mathbf{x}_{\text{incr}}$.

Ex1004, Figure 4-2. A POSITA would have understood that Olson provides a mathematical relationship between every node, including the initial location.

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

- o) **Claim 10: The system of claim 1, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.**

144. In my opinion, Olson discloses this limitation.

145. As explained in Sections VII.A.1.e, *l supra* (Element 1[b][2] and Claim 7), Olson discloses that each node has an uncertainty (or inversely a confidence) measure) which is provided at least by a probabilistic distribution (e.g., a posterior distribution or a Gaussian distribution). Ex1004, 12–13, 19–20, 22, 56; *see also* §§

VII.A.1.e, 1. A POSITA would have understood that the probabilistic distribution discloses a range of possible positions within which the node is located.

146. Olson further discloses that the confidence (or uncertainty) range of each one of the plurality of nodes is represented by the distribution's covariance ellipse which represents a region around each node, representing the range within which each pose (node) is likely to be found. Ex1004, 32; *see also* Ex1004, 118 (disclosing “range uncertainty” and “probability distributions resemble radially-oriented ellipses ... [and] [i]n practice, [can be] approximate[d] as a circle”).

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

p) Claim 11: The system of claim 1, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

148. In my opinion. Olson discloses this limitation.

149. As explained in Sections VII.A.1.e, 1, o *supra* (Element 1[b][2], Claim 7, and Claim 10), Olson discloses that each node in its pose/feature graph has an associated probabilistic distribution providing a range of possible positions within which the node is located and that such range is represented by a confidence region surrounding each node (e.g., an uncertainty ellipse-shaped or circular region surrounding each node) and, therefore, that the size of the range corresponds to the size of the confidence region representing it. 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*.”), 66 (disclosing covariance matrix of probabilistic distribution “estimates the relative confidence of each node”), 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.e, l, o.

150. Olson further discloses that the size of the confidence region of each node and, thus, the size of the range of each node (which is based on the size of the confidence region of the corresponding node) is variable. Ex1004, 66, 72. Olson indicates that the covariance matrix of probabilistic distribution “estimates the *relative* confidence of each node.” Ex1004, 66. Olson also explains that “some nodes are more uncertain than others” and that “a large decrease of χ^2 error can be obtained by distributing more error to less-confident nodes.” Ex1004, 66.

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

- q) **Claim 12: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.**

152. In my opinion, Olson discloses this limitation.

153. Olson describes known robots at the time such as the Roomba, a known cleaning robot that autonomously travels in an environment. Ex1004, 9. A POSITA would have known of the Roomba and its ability to move autonomously while cleaning.

154. Olson also explains that “map building is a critical component of almost every autonomous robot, particularly if they must operate in unfamiliar environments.” Ex1004, 9. Olson explains that it was improving upon existing map making techniques. Ex1004, 3, 16-17. A POSITA would understand that Olson’s techniques, including associating actions with poses (locations visited as the robot travels along the route) could be used with cleaning robots, such as the Roomba.

155. Therefore, it is my opinion that Olson discloses or renders obvious this limitation.

r) Element 13[pre]: A method for traveling a robot along a route, comprising:

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

157. The limitation was addressed in the discussion of Element 1[pre], and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.a.

s) Element 13[a]: collecting data by at least one sensor coupled to the robot as the robot travels along the route in an environment;

158. In my opinion, Olson discloses this limitation.

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

- t) **Element 13[b]: generating a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and**

160. In my opinion, Olson discloses this limitation.

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

- u) **Element 13[c]: associating actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.**

162. In my opinion, Olson discloses this limitation.

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

- v) **Claim 14: The method of claim 13, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the**

robot along the route in the environment and obstacles detected by the at least one sensor in the environment.

164. In my opinion, Olson discloses this limitation.

165. This limitation was addressed in the discussion of Claim 2, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.g.

w) Claim 15: The method of claim 13, further comprising estimating distance traveled by the robot along the route based on revolution of wheels on the robot.

166. In my opinion, Olson discloses this limitation.

167. 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.h.

x) Claim 16: The method of claim 13, further comprising: estimating distance traveled by the robot along the route based on sequential images captured by the at least one sensor.

168. In my opinion, Olson discloses this limitation.

169. This limitation was addressed in the discussion of Claim 4, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.i.

y) Claim 17: The method of claim 13, further comprising: determining the robot returned to a start position based on detecting a home locator in the environment.

170. In my opinion, Olson discloses this limitation.

171. This limitation was addressed in the discussion of Claim 5, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.j.

- z) Claim 18: The method of claim 13, further comprising: limiting uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.**

172. In my opinion, Olson discloses this limitation.

173. This limitation was addressed in the discussion of Claim 6, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.k.

- aa) Claim 19: The method of claim 13, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.**

174. In my opinion, Olson discloses this limitation.

175. This limitation was addressed in the discussion of Claim 7, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.l.

- bb) Claim 20: The method of claim 13, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.**

176. In my opinion, Olson discloses this limitation.

177. This limitation was addressed in the discussion of Claim 8, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.m.

- cc) Claim 21: The method of claim 13, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the**

position of the robot is relative to either an initial location or one or more features in the environment.

178. In my opinion, Olson discloses this limitation.

179. This limitation was addressed in the discussion of Claim 9, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.n.

dd) Claim 22: The method of claim 13, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.

180. In my opinion, Olson discloses this limitation.

181. This limitation was addressed in the discussion of Claim 10, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.o.

ee) Claim 23: The method of claim 13, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

182. In my opinion, Olson discloses this limitation.

183. This limitation was addressed in the discussion of Claim 11, and it is disclosed in Olson for substantially the same reasons. *See* § VII.A.1.p.

ff) Claim 24: “The method of claim 13, further comprising: actuating one or more systems selectively as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.”

184. In my opinion, Olson discloses this limitation.

185. This limitation was addressed in the discussion of Element 12, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.q.

gg) Element 25[pre]: A non-transitory computer readable medium comprising computer readable instructions stored thereon that when executed by at least one processing device configure the at least one processing device to,

186. In my opinion, Olson discloses this limitation.

187. This limitation was addressed in the discussion of Elements 1[pre], 1[a], and 13[pre] and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.a, b, r.

hh) Element 25[a]: collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment;

188. In my opinion, Olson discloses this limitation.

189. This limitation was addressed in the discussion of Elements 1[b][1] and 13[a], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.d, s.

ii) Element 25[b]: generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes

along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and

190. In my opinion, Olson discloses this limitation.

191. This limitation was addressed in the discussion of Elements 1[b][2] and 13[b], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.e, t.

jj) Element 25[c]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

192. In my opinion, Olson discloses this limitation.

193. This limitation was addressed in the discussion of Elements 1[b][3] and 13[c], and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.f, u.

kk) Claim 26: The non-transitory computer readable medium of claim 25, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.

194. In my opinion, Olson discloses this limitation.

195. This limitation was addressed in the discussion of Claims 2 and 14, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.g, v.

ll) Claim 27: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.

196. In my opinion, Olson discloses this limitation.

197. This limitation was addressed in the discussion of Claims 3 and 15, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.h, w.

mm) Claim 28: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.

198. In my opinion, Olson discloses this limitation.

199. This limitation was addressed in the discussion of Claims 4 and 16, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.i, x.

nn) Claim 29: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, determine the robot has returned to a start position based on detecting a home locator in the environment.

200. In my opinion, Olson discloses this limitation.

201. This limitation was addressed in the discussion of Claims 5 and 17, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.j, y.

oo) Claim 30: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.

202. In my opinion, Olson discloses this limitation.

203. This limitation was addressed in the discussion of Claims 6 and 18, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.k, z.

pp) Claim 31: The non-transitory computer readable medium of claim 30, wherein each node of the plurality of nodes include an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.

204. In my opinion, Olson discloses this limitation.

205. This limitation was addressed in the discussion of Claims 7 and 19, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.l, aa.

qq) Claim 32: The non-transitory computer readable medium of claim 25, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.

206. In my opinion, Olson discloses this limitation.

207. This limitation was addressed in the discussion of Claims 8 and 20, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.m, bb.

rr) Claim 33: The non-transitory computer readable medium of claim 25, wherein each one of the plurality

of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.

208. In my opinion, Olson discloses this limitation.

209. This limitation was addressed in the discussion of Claims 9 and 21, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.n, cc.

ss) Claim 34: The non-transitory computer readable medium of claim 25, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.

210. In my opinion, Olson discloses this limitation.

211. This limitation was addressed in the discussion of Claims 10 and 22, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.o, dd.

tt) Claim 35: The non-transitory computer readable medium of claim 25, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

212. In my opinion, Olson discloses this limitation.

213. This limitation was addressed in the discussion of Claims 11 and 23, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.p, ee.

uu) “The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels the route, the one or more systems comprises a cleaning system, the

cleaning system comprises one or more of water flow, brush, and vacuum cleaner.”

214. In my opinion, Olson discloses this limitation.

215. This limitation was addressed in the discussion of Claims 12 and 24, and it is disclosed in Olson for substantially the same reasons. *See* §§ VII.A.1.q, ff.

B. Ground 2: Claims 1–11, 13–23, and 25–36 are Anticipated by Stachniss

216. In my opinion, claims 1–11, 13–23, and 25–36 of the ’576 patent are anticipated by Stachniss.

1. Element-by-Element Analysis

a) Element 1[pre]: A system for traveling a robot along a route, comprising:

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

218. Stachniss discloses a system 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.

219. 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.

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

Ex1005, 1153.

221. Stachniss discloses robots that store 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 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*.”).

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

b) Element 1[a]: a memory having computer readable instructions stored thereon; and

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

224. 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, 1153–54, 1164. A POSITA would have understood that the robots disclosed in Stachniss capable of implementing the solution(s) disclosed in Stachniss would have a memory with computer readable instructions stored thereon.

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

c) Element 1[b]: at least one processing device configurable to execute the computer readable instructions to,

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

227. Stachniss discloses a “graphical processing unit (GPU)” that allows for processing a three-dimensional map. Ex1005, 1169. Stachniss also discloses a robot processing data, such as mathematical models, which means they must have a processing device configurable to execute the computer readable instructions. Ex1005, 1154–1155, 1157–62. 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 optimize the graph incrementally after each new node is added, and can perform “relative optimization . . . aim[ed] at computing locally consistent geometric maps.” Ex1005, 1155, 1164–65.

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

d) Element 1[b][1]: collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment,

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

230. 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 .

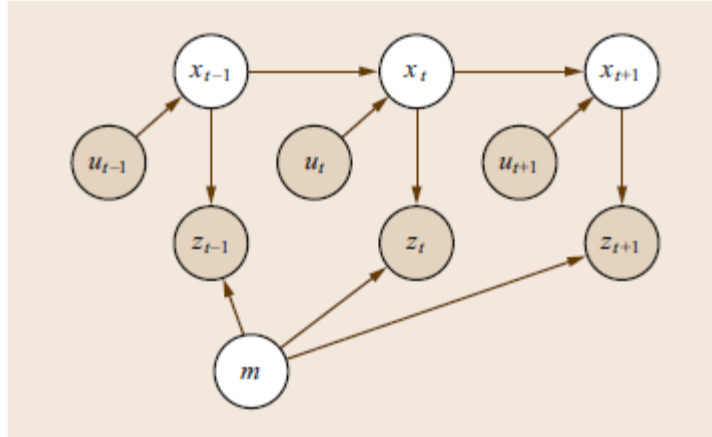


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

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

- e) **Element 1[b][2]: generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and**

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

233. Stachniss discloses that a robot can create a map of an environment and a route (sequence of robot's locations or path) on the map in real-time based on sensor measurements. Ex1004, 1162–66. 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.

234. The result is depicted in Fig. 46.7a-c, reproduced below.

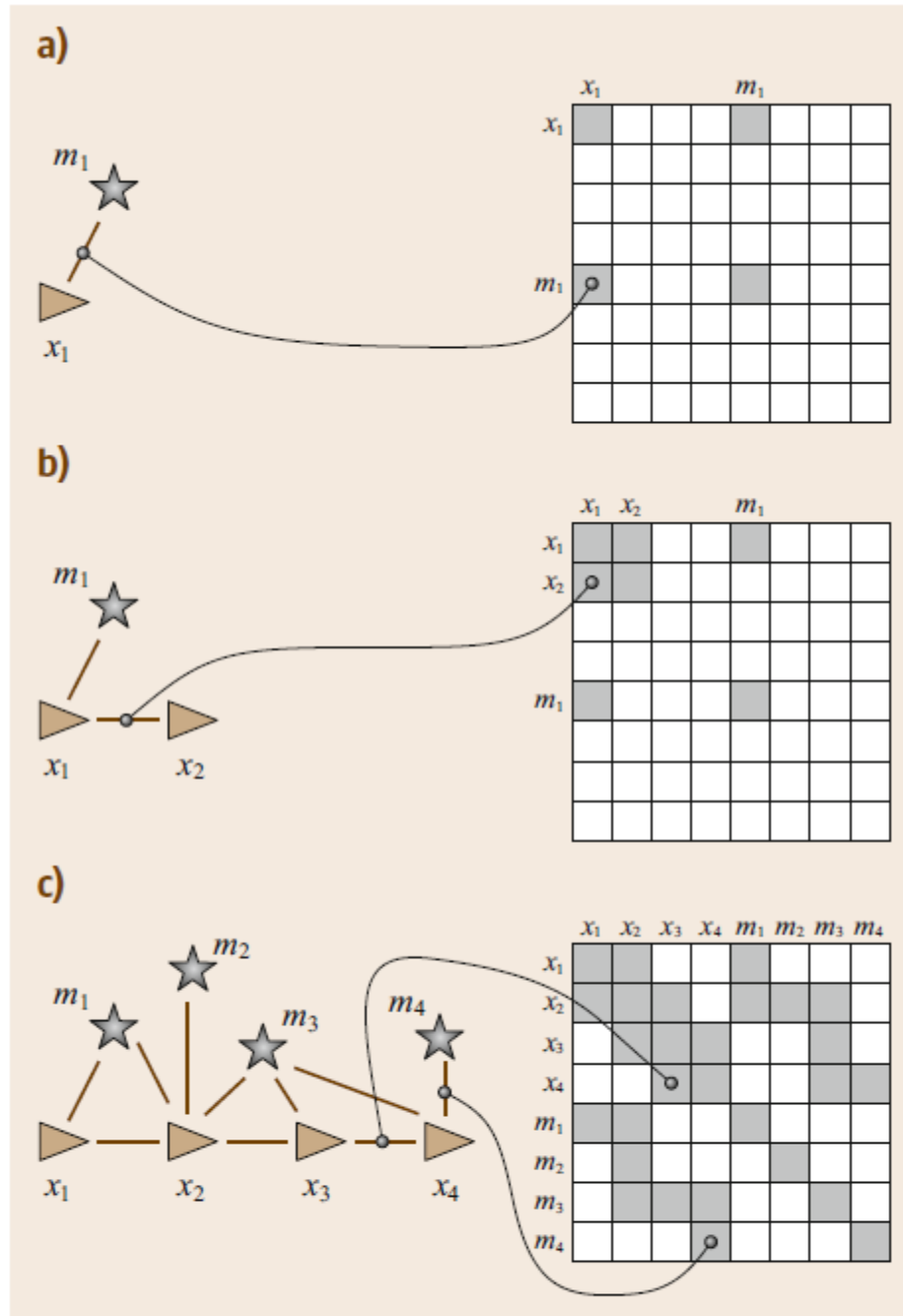


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a-c.

235. As also discussed with respect to Element 1[b][1] in Section VII.B.1.d *supra*, the robot can optimize the estimated map and the estimated sequence of robot's locations (route along map), with the use of odometry and visual sensor data to get the most reliable estimates possible for the map and sequence of robot's locations (route along map). Ex1005, 1153–1155, 1164; *see also* § VII.B.1.d.

236. Stachniss also discloses that the map is generated while the robot moves along a route. Ex1005, 1154. In fact, and as explained in the “Background Technology” section (*see* § IV *supra*), SLAM stands for ***Simultaneous*** Localization and Mapping. Ex1005, 1153. For example, Stachniss discloses “incremental versions that effectively re-use the previously computed solution have been proposed” to reduce processing requirements. Ex1005, 1162. For example, the robot may “build[] 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 [*i.e.*, at each new node] during mapping.” Ex1005, 1164.

237. Stachniss further discloses real-time online mapping. Ex1005, 1164–67. For example, Stachniss discloses SLAM techniques that “use hierarchical data structures [] and pose-graphs [] combined with a lazy optimization for **on-the-fly** mapping.” Ex1005, 1164–1165; *see also* Table 46.1 (indicating “on-the-fly processing.”). Further, Stachniss discloses a “real-time SLAM system that operated

with a single freely moving camera as the only data source.” Ex1005, 1166. Figure 46.11 (reproduced below) in Stachniss is an example of a map generated in real-time.

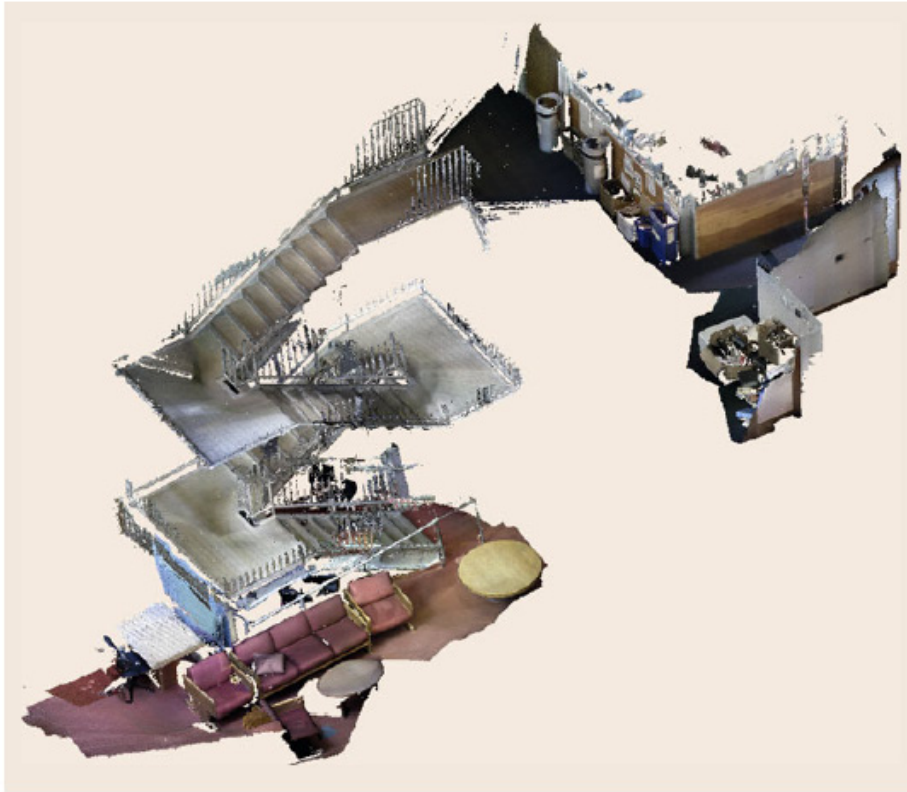


Fig. 46.11 Spatially extended KinectFusion output produced in real-time with Kintinuous (after [46.139])

Ex1005, Fig. 46.11.

238. In addition, Stachniss discloses that each node has an uncertainty measure or a confidence range associated with it. 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 $\mathbf{R}_t$.

239. For a system that implements graph-SLAM methods using sensor data, Stachniss further discloses an equation that corresponds to the log of the posterior probability distribution (reproduced below) that incorporates uncertainty (noise), in the sensed environment feature data (e.g., visual sensor data), also denoted as feature observation data. Ex1005, 1163.

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

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”).

240. 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,

1157-1158 (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.

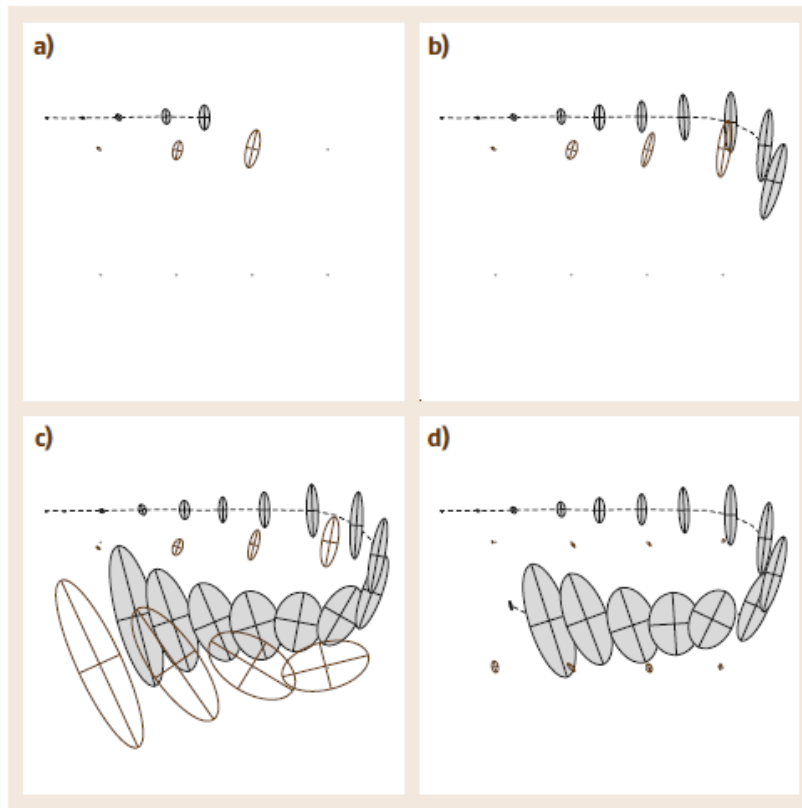


Fig.46.2a-d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a-c) the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

241. 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 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).

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

f) Element 1[b][3]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

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

244. As explained with respect to Element 1[b][1] in Section VII.B.1.d *supra*, Stachniss discloses a pose graph which is generated by associating location and position of a robot to sensor data. *See* § VII.B.1.d. The robot moves from one position to another according to “controls given to [robot] motors.” Ex1005, 1154. These instructions may be measured and/or verified by onboard odometry sensors and logged in association with a given node (*e.g.*, u_t with x_t). Ex1005, 1154. These movements are actions undertaken by the robot during traveling along the route, and they are associated with the location and position of the robot along the route on the map.

245. Further, the robot takes sensor measurements at each location and associates the results of those sensor measurements with the node. These sensors include odometers, lasers, range sensors, cameras, and RGB-D sensors. Ex1005,

1153–54, 1158–59, 1163–64, 1166–69. The data collected by the sensors is used to provide information regarding the nodes and edges between the nodes. Ex1005, 1154, 1158–59, 1162–64, 1166–69. For example, wheel odometry data (u_t) can provide information such as distance between the sequence of pose nodes (x_t); such information is represented by edges between consecutive pose nodes. Furthermore, sensor scans (z_t) can provide information about landmarks (represented by landmark nodes) that can be observed by a robot from each of its locations x_t , (represented by pose nodes); such information is indicated by edges between a pose node and the observable landmarks from that pose node. Ex1005, 1154, 1158–59, 1162–64, 1166–69. This is depicted in Figures 46.1 and 46.7, reproduced below. The act of taking measurements and the results of these measurements are actions undertaken by the robot during traveling along the route, and they are associated with the location and position of the robot along the route on the map.

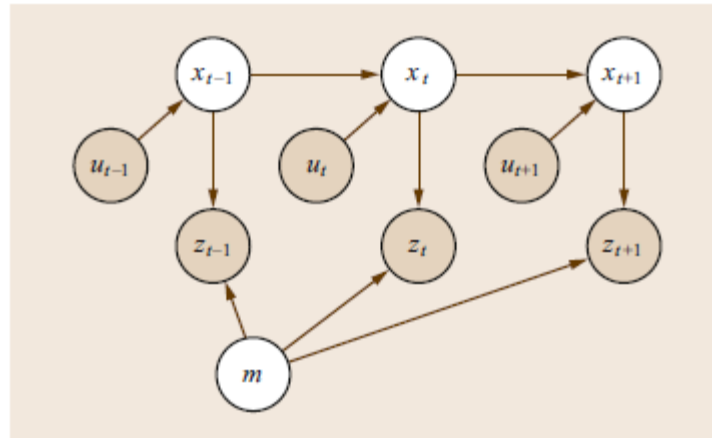


Fig. 46.1 Graphical model of the SLAM problem. Arcs indicate causal relationships, and shaded nodes are directly observable to the robot. In SLAM, the robot seeks to recover the unobservable variables

Ex1005, Fig. 46.1.

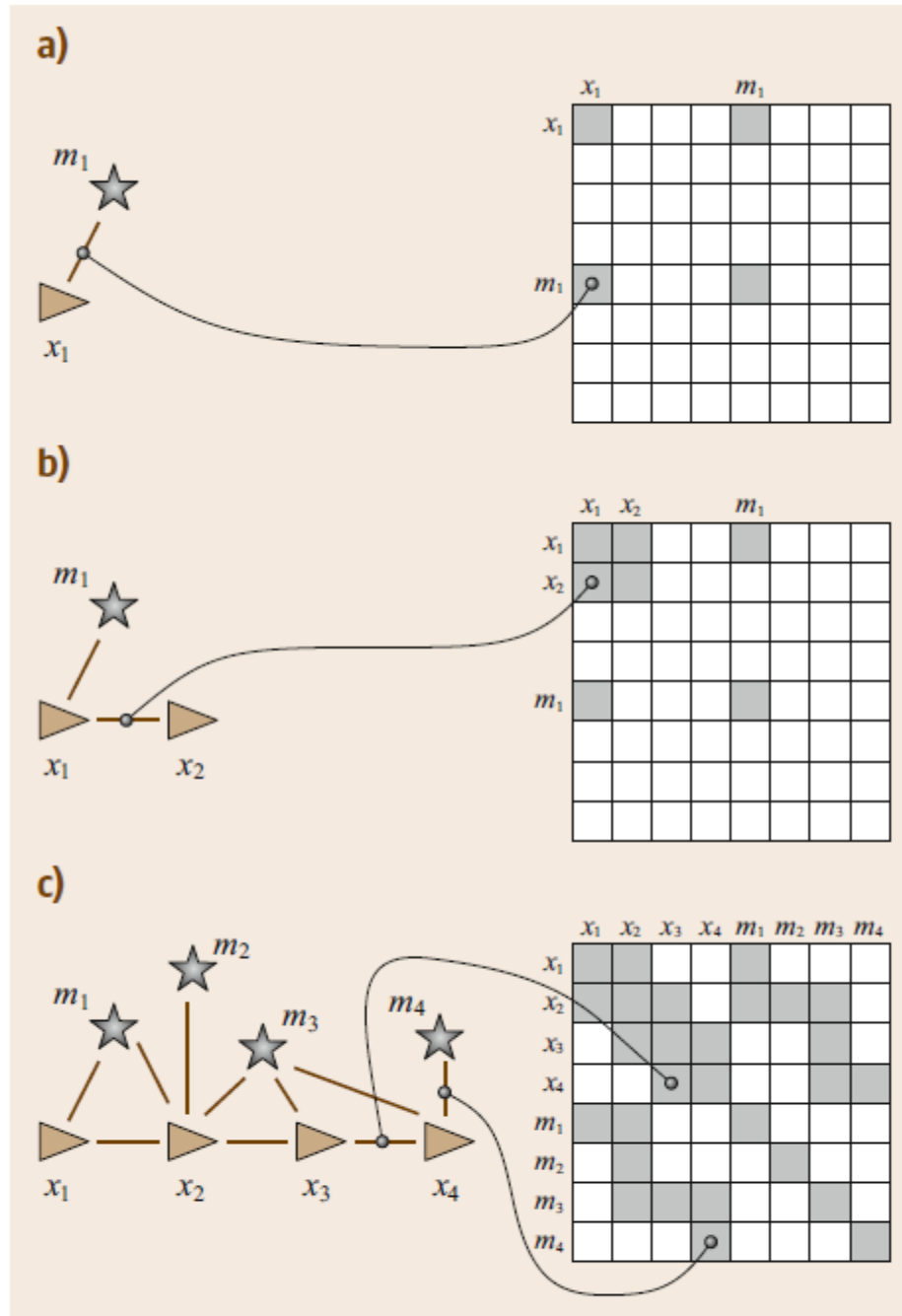


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a-c.

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

- g) Claim 2: The system of claim 1, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.**

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

248. Stachniss explains that the map is either a two-dimensional or three-dimensional representation of the environment. With respect to two-dimensional representations, Stachniss explains that “[w]hen building 2-D maps, point-landmarks may correspond to door posts and corners of rooms, which, when projected into a 2-D map are characterized by a point coordinate. In a 2-D world, each point-landmark is characterized by two coordinate values.” Ex1005, 1155. And with respect to three-dimensional representations, Stachniss explains that “[v]isual sensors offer a wealth of information that enables the construction of rich 3-D models [(maps)] of the world.” Ex1005, 1166. Stachniss continues to provide examples of maps enabled by visual sensors like RGB-D sensors: “[s]everal compelling 3-D mapping and localization have been created in recent years with RGB-D (Kinect) sensors. The combination of direct range measurements with dense visual imagery can enable dramatic improvements in mapping and navigation systems for indoor environments. State-of-the-art RGB-D SLAM systems include [46.109] and [46.86]. Figure 46.9 shows examples of the output of these systems.”

Ex1005, 1168. Stachniss provides examples of 2-D and 3-D maps in Figures 46.8 and 46.11 (reproduced below), respectively.

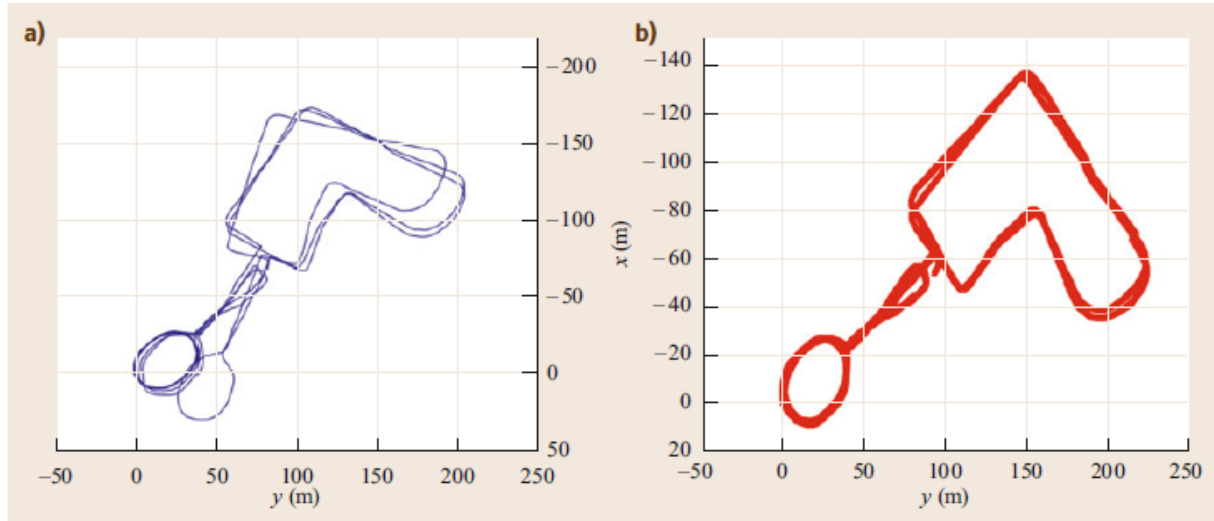


Fig. 46.8 (a) A 2-km path and 50 000 frames estimated for the New College Dataset (after [46.117]) using relative bundle adjustment (after [46.98]). (b) the relative bundle adjustment solution is easily improved by taking FAB-MAP (after [46.118]) loop-closures into account – this is achieved without global optimization (after [46.119]). Sibley et al. advocate that relative metric accuracy and topological consistency are the requirements for autonomous navigation, and these are better achieved using a relative manifold representation instead of using a conventional single Euclidean representation [46.120]

Ex1005, Fig. 46.8.

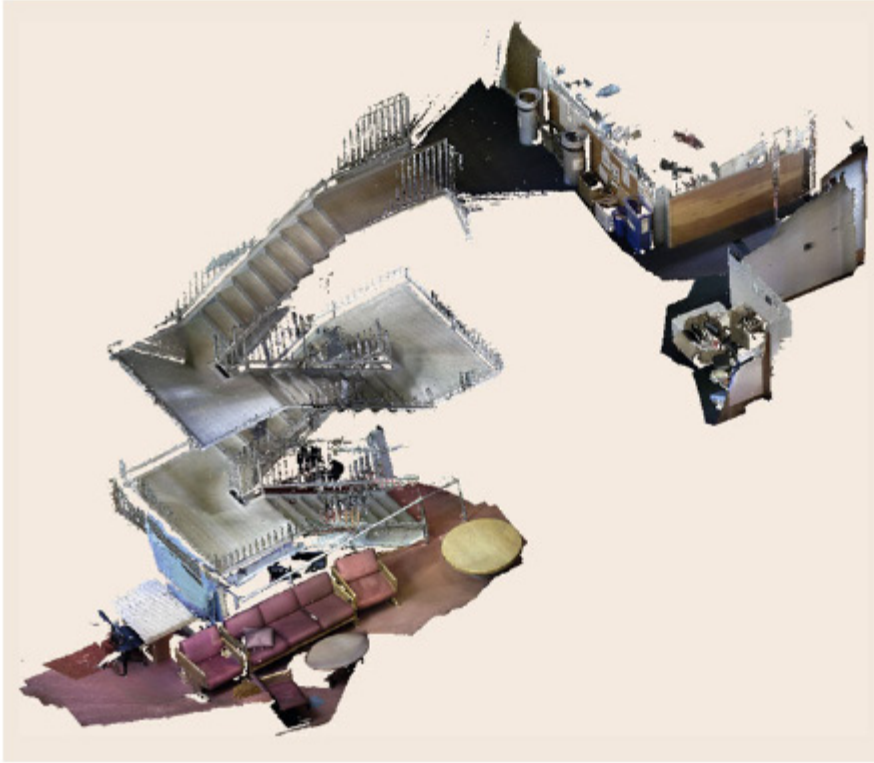


Fig. 46.11 Spatially extended KinectFusion output produced in real-time with Kintinuous (after [46.139])

Ex1005, Fig. 46.11.

249. As explained in Section VII.B.1.e *supra*, the map also includes a pose-graph, which includes information directed to the position and location of the robot as it travels along the route. *See* § VII.B.1.e.

250. Stachniss also discloses that the map its robot generates includes the position and location of obstacles in the environment. For example, Stachniss explains that a 2-D map may include “point-landmarks [obstacles], [which] correspond to door posts and corners of rooms.” Ex1005, 1155. Stachniss uses these landmarks to localize the robot and generate the map. Ex1005, 1157–66. Stachniss further explains that “dense visual imagery can enable dramatic improvements in mapping and navigation systems for indoor environments,” such as the map depicted

in Figure 46.11 (reproduced above), which shows obstacles like tables and chairs at various positions within the map. Ex1005, 1168–69.

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

h) Claim 3: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.

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

253. As explained with respect to Element 1[b] in Section VII.B.1.c *supra*, Stachniss discloses a robot with a processing device configurable to execute computer readable instructions. *See* § VII.B.1.c.

254. Stachniss further discloses that a robot may estimate distance traveled by the robot along the route based on revolution of wheels on the robot. For example, Stachniss explains that “[o]dometry provides relative information between two consecutive locations. . . . such data may be obtained from the robot’s wheel encoders.” Ex1005, 1154–55. Wheel encoders measure at least the revolution of wheels to estimate distance. Stachniss explains that this odometry may be used to estimate positions of the robot (distance traveled) along a route, as depicted in Fig. 46.5 (reproduced below). Ex1005, 1161. Stachniss further explicitly explains that odometry data may be used in graph-based methods. Ex1005, 1162–63.

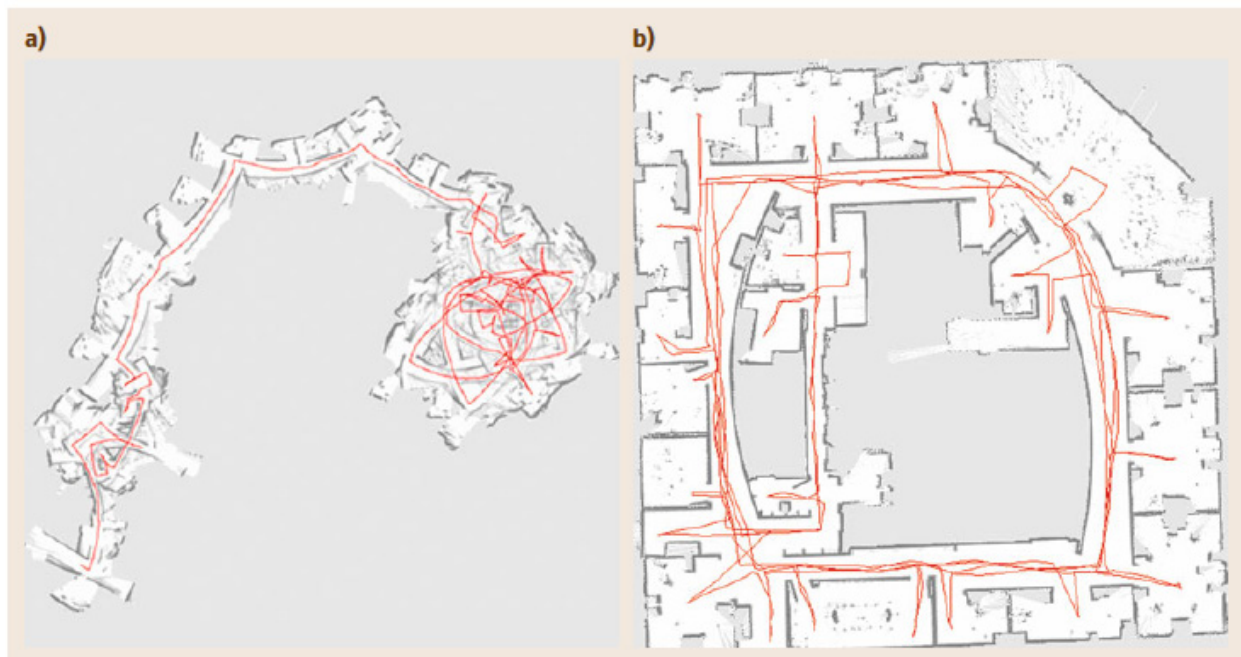


Fig. 46.5 Occupancy grid map generated from laser range data and based on pure odometry (image courtesy of Dirk Hähnel, University of Freiburg)

Ex1005, Fig. 46.5.

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

- i) **Claim 4: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.**

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

257. As explained with respect to Element 1[b] in Section VII.B.1.c *supra*, Stachniss discloses a robot with a processing device configurable to execute computer readable instructions. *See* § VII.B.1.c.

258. Stachniss further explains that a robot may use “visual odometry” 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.

259. 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. 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 sequential 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, in 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 standard 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.

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

j) Claim 5: The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, determine the robot returned to a start position based on detecting a home locator in the environment.

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

262. As explained with respect to Element 1[b] in Section VII.B.1.c *supra*, Stachniss discloses a robot with a processing device configurable to execute computer readable instructions. *See* § VII.B.1.c.

263. 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.”

264. 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 .

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

265. 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.

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

- k) Claim 6: The system of claim 1, wherein the least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.**

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

268. As explained with respect to Element 1[b] in Section VII.B.1.c *supra*, Stachniss discloses a robot with a processing device configurable to execute computer readable instructions. *See* § VII.B.1.c.

269. As explained with respect to Claim 5 in Section VII.B.1.j *supra*, Stachniss discloses a robot that performs loop closures. *See* § VII.B.1.j. Loop closures reduce the uncertainty of the map by determining that the robot has “reach[ed] the same location.” Ex1005, 1156–58. The algorithm may additionally impose an absolute constraint by eliminating the end pose (position) 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.

270. 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.

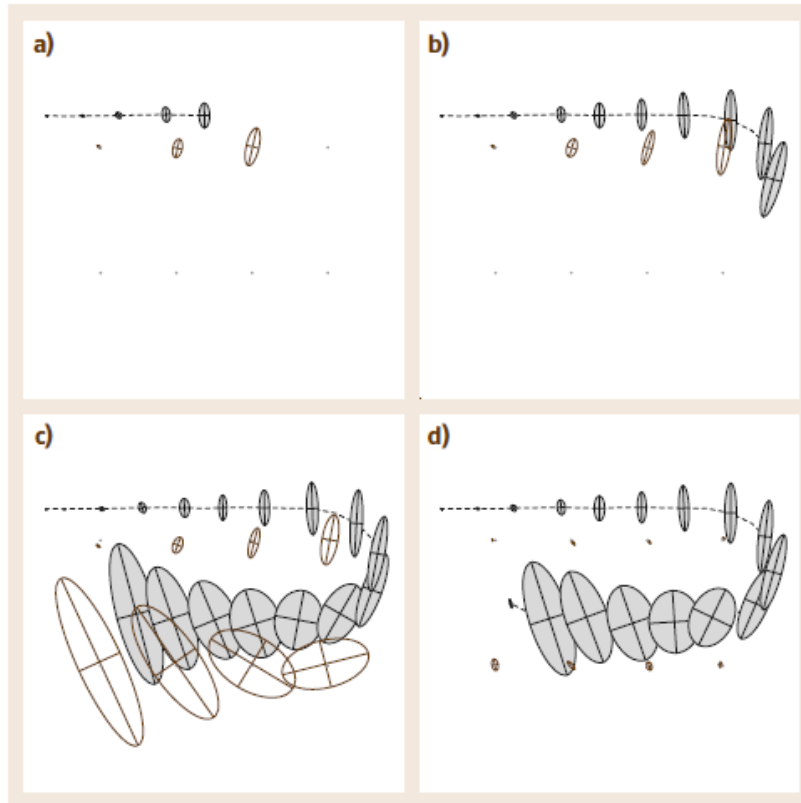


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In **(a–c)**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

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

- l) Claim 7: The system of claim 6, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which corresponds to surrounding region around each node of the plurality of nodes.**

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

273. 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, 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: $p(x_t \mid x_{t-1}, u_t)$ 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, $p(z_t \mid x_t, m)$ 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.

274. 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.

275. 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_t)] 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, as depicted in Fig. 46.2a–d (reproduced below).

Ex1005, 1158.

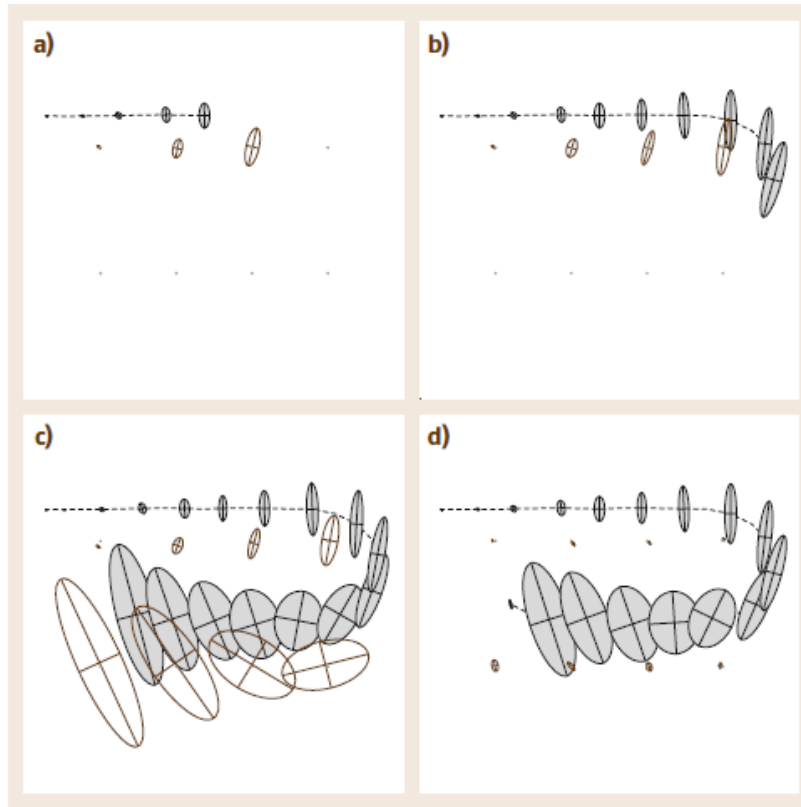


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In **(a–c)**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

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

m) Claim 8: The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.

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

278. As explained with respect to Element 1[b][2] in Section VII.B.1.e *supra*, Stachniss discloses that each pose in the pose-graph is a node along the route traveled by the robot. See § VII.B.1.e.

279. As explained with respect to claim 7 in Section VII.B.1.1 *supra*, each node corresponds to a probabilistic function/distribution. See § VII.B.1.1. Stachniss further explains that each node may correspond to a Gaussian distribution, a type of probabilistic distribution. Ex1005, 1155, 1158, 1166.

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

n) **Claim 9: The system of claim 1, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.**

281. In my opinion, Stachniss discloses “wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.”

282. As explained with respect to Element 1[b][2] in Section VII.B.1.e *supra*, Stachniss discloses that each position of the robot is represented by a node. See § VII.B.1.e. Further, Stachniss discloses “[a] mobile robot roams an unknown environment, starting at an initial location x_0 .” 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.

283. 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.

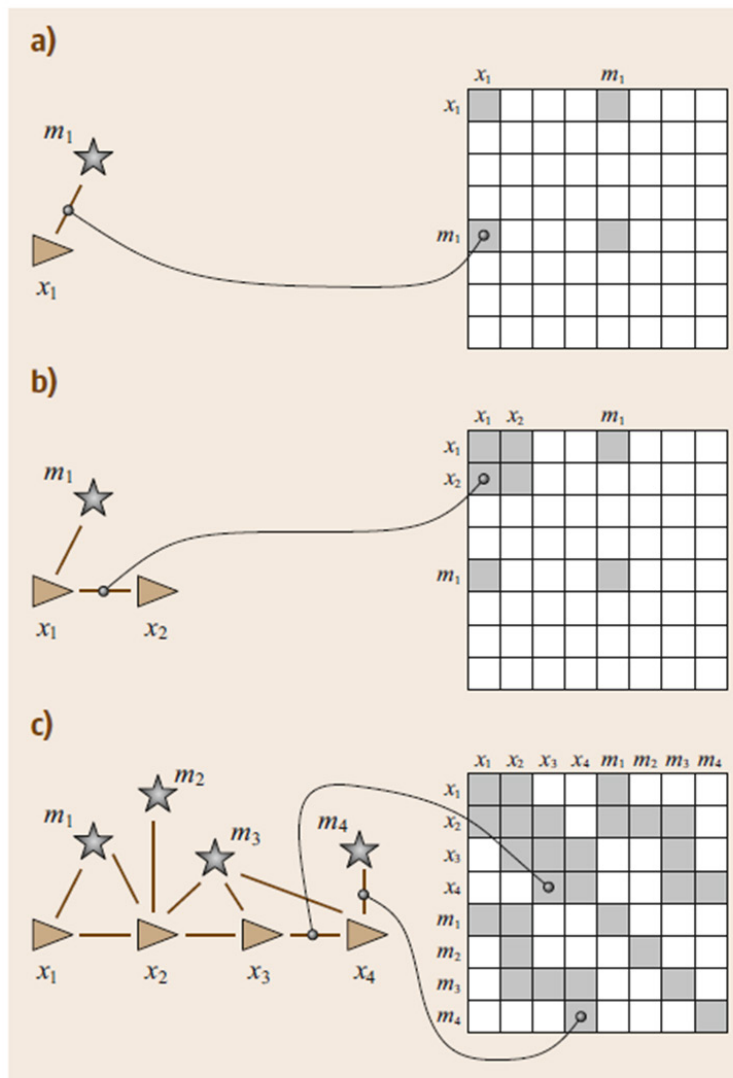


Fig.46.7a-c Illustration of the graph construction. The **(a)** diagram shows the graph, the **(b)** the constraints in matrix form. **(a)** Observation is landmark m_1 . **(b)** Robot motion from x_1 to x_2 . **(c)** Several steps later

Ex1005, Fig. 46.7a–c.

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

- o) Claim 10: The system of claim 1, wherein the range of each one of the plurality of nodes corresponds to a**

region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.

285. In my opinion, Stachniss discloses “wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.”

286. As explained in Sections VII.B.1.e, k–m *supra*, Stachniss discloses that each node has a corresponding probability distribution which acts as a range of uncertainty or range of confidence regarding the true location. Ex1005, 1155, 1157–58, 1163; *see also* §§ VII.B.1.e, k–m. This is because noise can make it difficult for sensors to get an exact location. Ex1005, 1155, 1157–58, 1163. The true robot’s location as well as the estimated robot’s location (represented by each of the pose nodes in the graph) are within the distribution range, which is shown as a region around each node in Fig, 46.2a–d, reproduced below. Ex1005, 1155, 1157–58, 1163, Fig. 46.2a–d. As shown in Fig, 46.2a–d, each node has a range, represented by an ellipse around each of the nodes. Ex1005, 1158, Fig, 46.2a–d. The larger the range, the bigger the ellipses and vice versa. Ex1005, 1158.

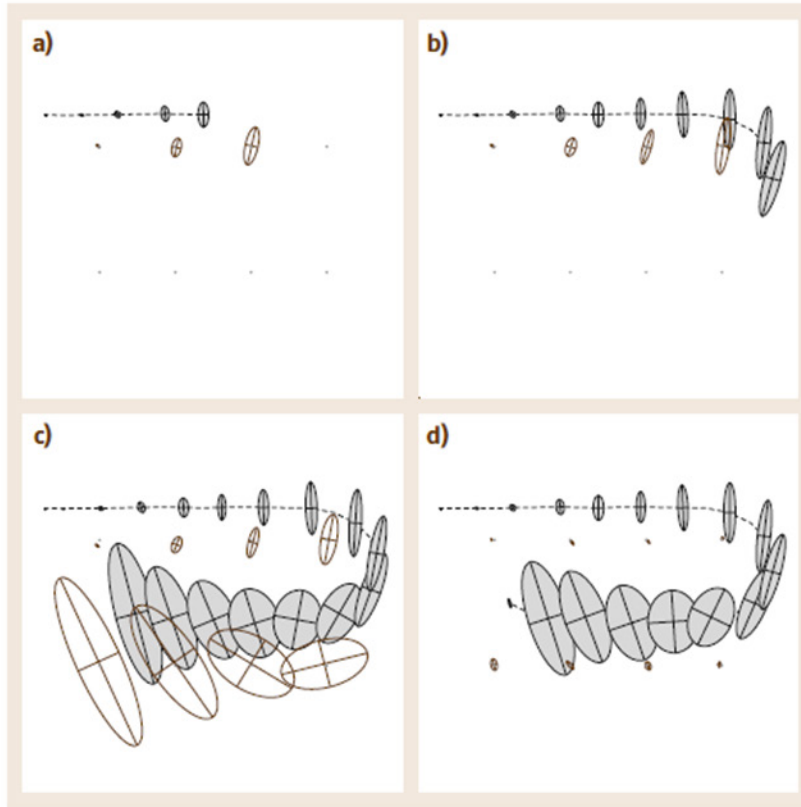


Fig.46.2a-d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a-c) the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

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

p) Claim 11: The system of claim 1, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

288. In my opinion, Stachniss discloses “wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.”

289. As explained in Sections VIII.B.1.e, k-m, o *supra*, each node has a confidence range regarding the true location of the node. Ex1005, 1155, 1157-58,

1163; *see also* §§ VIII.B.1.e, k–m, o. At each node, as the uncertainty increases, the size of the range also increases and vice versa. Ex1005, 1157–58, Fig. 46.2a–d.

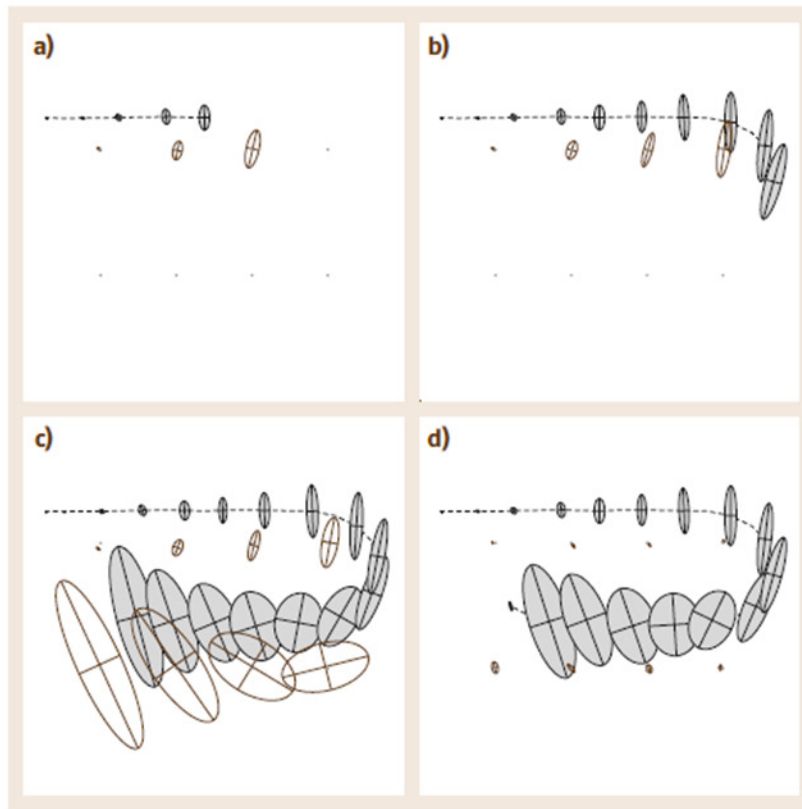


Fig.46.2a–d EKF applied to the online SLAM problem. The robot's path is a *dotted line*, and its estimates of its own position are *shaded ellipses*. Eight distinguishable landmarks of unknown location are shown as *small dots*, and their location estimates are shown as *white ellipses*. In (a–c) the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

290. The confidence range for a single node is related to other nodes in the path. Ex1005, 1158. For example, as seen in Figure 46.2a–d, the further the node is from the starting location, the larger the ellipses (greater the uncertainty). Ex1005, 1158. Similarly, as demonstrated in 46.2d, once more information is known about a single node, such as when the robot closes a loop, the uncertainty for each of the nodes is affected and can be reduced (*i.e.*, the size of the ellipses gets smaller). Ex1005, 1158, 1163.

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

q) Element 13[pre]: A method for traveling a robot along a route, comprising:

292. In my opinion, Stachniss discloses this limitation.

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

r) Element 13[a]: collecting data by at least one sensor coupled to the robot as the robot travels along the route in an environment;

294. In my opinion, Stachniss discloses this limitation.

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

s) Element 13[b]: generating a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and

296. In my opinion, Stachniss discloses this limitation.

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

- t) **Element 13[c]: associating actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.**

298. In my opinion, Stachniss discloses this limitation.

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

- u) **Claim 14: The method of claim 13, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.**

300. In my opinion, Stachniss discloses this limitation.

301. This limitation was addressed in the discussion of Claim 2, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.g.

- v) **Claim 15: The method of claim 13, further comprising estimating distance traveled by the robot along the route based on revolution of wheels on the robot.**

302. In my opinion, Stachniss discloses this limitation.

303. 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.h.

- w) **Claim 16: The method of claim 13, further comprising: estimating distance traveled by the robot along the route based on sequential images captured by the at least one sensor.**

304. In my opinion, Stachniss discloses this limitation.

305. This limitation was addressed in the discussion of Claim 4, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.i.

- x) **Claim 17: The method of claim 13, further comprising: determining the robot returned to a start position based on detecting a home locator in the environment.**

306. In my opinion, Stachniss discloses this limitation.

307. This limitation was addressed in the discussion of Claim 5, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.j.

- y) **Claim 18: The method of claim 13, further comprising: limiting uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.**

308. In my opinion, Stachniss discloses this limitation.

309. This limitation was addressed in the discussion of Claim 6, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.k.

- z) **Claim 19: The method of claim 13, wherein each node of the plurality of nodes comprises an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.**

310. In my opinion, Stachniss discloses this limitation.

311. This limitation was addressed in the discussion of Claim 7, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.l.

- aa) **Claim 20: The method of claim 13, wherein each one of the plurality of nodes along the route traveled by**

the robot corresponds to a probabilistic function or probabilistic distribution.

312. In my opinion, Stachniss discloses this limitation.

313. This limitation was addressed in the discussion of Claim 8, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.m.

bb) Claim 21: The method of claim 13, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.

314. In my opinion, Stachniss discloses this limitation.

315. This limitation was addressed in the discussion of Claim 9, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.n.

cc) Claim 22: The method of claim 13, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.

316. In my opinion, Stachniss discloses this limitation.

317. This limitation was addressed in the discussion of Claim 10, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.o.

dd) Claim 23: The method of claim 13, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

318. In my opinion, Stachniss discloses this limitation.

319. This limitation was addressed in the discussion of Claim 11, and it is disclosed in Stachniss for substantially the same reasons. *See* § VII.B.1.p.

ee) Element 25[pre]: A non-transitory computer readable medium comprising computer readable instructions stored thereon that when executed by at least one processing device configure the at least one processing device to,

320. In my opinion, Stachniss discloses this limitation.

321. This limitation was addressed in the discussion of Elements 1[pre], 1[a], and 13[pre] and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.a, b, q.

ff) Element 25[a]: collect data by at least one sensor coupled to the robot as the robot travels along the route in an environment;

322. In my opinion, Stachniss discloses this limitation.

323. This limitation was addressed in the discussion of Elements 1[b][1] and 13[a], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.d, r.

gg) Element 25[b]: generate a map of the environment and a route on the map in real-time, the map being generated concurrently with the collection of the data as the robot travels along the route in the environment, the map corresponding to a representation of the environment, the map including information directed to location and position of the robot along the route in the environment, the map being generated based on measurements taken by the at least one sensor at each one of a plurality of nodes

along the route traveled by the robot, each one of the plurality of nodes comprising a range, the range of each one of the plurality of nodes being based on confidence measure at a respective node, and

324. In my opinion, Stachniss discloses this limitation.

325. This limitation was addressed in the discussion of Elements 1[b][2] and 13[b], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.e, s.

hh) Element 25[c]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

326. In my opinion, Stachniss discloses this limitation.

327. This limitation was addressed in the discussion of Elements 1[b][3] and 13[c], and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.f, t.

ii) Claim 26: The non-transitory computer readable medium of claim 25, wherein the map is either a two-dimensional or three-dimensional representation of the environment, the map includes information directed to location and position of the robot along the route in the environment and obstacles detected by the at least one sensor in the environment.

328. In my opinion, Stachniss discloses this limitation.

329. This limitation was addressed in the discussion of Claims 2 and 14, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.g, u.

jj) Claim 27: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on revolution of wheels on the robot.

330. In my opinion, Stachniss discloses this limitation.

331. This limitation was addressed in the discussion of Claims 3 and 15, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.h, v.

kk) Claim 28: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, estimate distance traveled by the robot along the route based on sequential images captured by the at least one sensor.

332. In my opinion, Stachniss discloses this limitation.

333. This limitation was addressed in the discussion of Claims 4 and 16, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.i, w.

ll) Claim 29: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, determine the robot has returned to a start position based on detecting a home locator in the environment.

334. In my opinion, Stachniss discloses this limitation.

335. This limitation was addressed in the discussion of Claims 5 and 17, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.j, x.

mm) Claim 30: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.

336. In my opinion, Stachniss discloses this limitation.

337. This limitation was addressed in the discussion of Claims 6 and 18, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.k, y.

nn) Claim 31: The non-transitory computer readable medium of claim 30, wherein each node of the plurality of nodes include an associated probabilistic distribution which correspond to surrounding region around each node of the plurality of nodes.

338. In my opinion, Stachniss discloses this limitation.

339. This limitation was addressed in the discussion of Claims 7 and 19, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.l, z.

oo) Claim 32: The non-transitory computer readable medium of claim 25, wherein each one of the plurality of nodes along the route traveled by the robot corresponds to a probabilistic function or probabilistic distribution.

340. In my opinion, Stachniss discloses this limitation.

341. This limitation was addressed in the discussion of Claims 8 and 20, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.m, aa.

pp) Claim 33: The non-transitory computer readable medium of claim 25, wherein each one of the plurality

of nodes along the route traveled by the robot corresponds to position of the robot, the position of the robot is relative to either an initial location or one or more features in the environment.

342. In my opinion, Stachniss discloses this limitation.

343. This limitation was addressed in the discussion of Claims 9 and 21, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.n, bb.

qq) Claim 34: The non-transitory computer readable medium of claim 25, wherein the range of each one of the plurality of nodes corresponds to a region around each one of the plurality of nodes such that each one of the plurality of nodes is located within the range.

344. In my opinion, Stachniss discloses this limitation.

345. This limitation was addressed in the discussion of Claims 10 and 22, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.o, cc.

rr) Claim 35: The non-transitory computer readable medium of claim 25, wherein size of the range of each one of the plurality of nodes is variable based on confidence in location of each node of the plurality of nodes.

346. In my opinion, Stachniss discloses this limitation.

347. This limitation was addressed in the discussion of Claims 11 and 23, and it is disclosed in Stachniss for substantially the same reasons. *See* §§ VII.B.1.p, dd.

C. Grounds 3 and 4: Claims 1–36 are Rendered Obvious in View of Olson or Stachniss in Combination with Fong

348. It is my opinion that to the extent that either Olson or Stachniss does not disclose claims 1–36, 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

349. 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.

350. 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, 1157-1169. 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

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

a) Element 1[a]: a memory having computer readable instructions stored thereon; and

352. 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 “a memory having computer readable instructions stored therein.”

353. Fong explicitly discloses “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, 2:59-3:3. Fong also explicitly states that:

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.

354. 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. A POSITA would have known that a mobile autonomous robot contained a memory having computer readable instructions stored within as it was standard practice for a robot to contain one.

355. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

b) Element 1[b]: at least one processing device configurable to execute the computer readable instructions to,

356. 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 “at least one processing device configurable to execute the computer readable instructions.”

357. Fong explicitly discloses:

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.

358. It is also my opinion that it would have been obvious to a POSITA to combine Olson or Stachniss with Fong. Robots routinely have a processor or microprocessor to carry out commands, make calculations and determinations. A POSITA would have known that a robot that moved autonomously contained a processor configurable to execute the computer readable instructions as it was standard practice for a robot to contain one.

359. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

c) Element 1[b][3]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

360. 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 “associate actions undertaken by the robot traveling along the route with the location and position of the robot on the route of the map.”

361. Fong discloses a robot that can “uniquely identify rooms (e.g., Zone A, Zone B, Zone C) by combining (1) identity information ... (2) RSSI... and (3) remote control.” Ex1006, 6:36–44; *see also* 4:59–63. Further, the robot can associate specific demands based on the location. Ex1006, 6:64–7:2.

For example, the robot may be executing a floor cleaning operation and the system 100 (e.g., via instructions from the hub 110 to the robot 200) may instruct the robot 200 to return to the dock 600, move to a different, unoccupied zone, avoid the occupied zone, or assume a quieter mode of operation.

Ex1006, 6:64-7:2.

362. It is also my opinion that it would have been obvious to a POSITA to combine Olson or Stachniss with Fong. A POSITA would see the benefits of having a robot behave differently in different locations. For example, it may be desirable for a robot to be on a quieter mode in a bedroom, or to use a mop instead of a vacuum on a wood floor. A POSITA would also have had a reasonable expectation of success in combining this feature in Fong with Olson or Stachniss because it was routine to give robots functions based on inputs such as location or pose. It would not be difficult for a POSITA to implement such functionality along with the functionality described in Olson or Stachniss.

363. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

d) Claim 5: wherein the least one processing device is further configurable to execute the computer readable instructions to, determine the robot returned to a start position based on detecting a home locator in the environment.

364. 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 “wherein the least one processing device is further configurable to execute the computer readable instructions to, determine the robot returned to a start position based on detecting a home locator in the environment.”

365. 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.

366. Further, Fong discloses that the robot is able to find the dock with the use of fiducial markers.

[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.

These fiduciary markers (home locator) allow the robot to determine if it returned to the dock.

367. 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 home dock as described in Fong.

368. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

- e) **Claim 6: wherein the least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.**

369. 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 “wherein the least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.”

370. Fong explicitly discloses:

In some embodiments, and according to the invention, a mobile robot system is provided that includes a docking station having at least two pose-defining fiducial markers. The pose-defining fiducial markers have a predetermined spatial relationship with respect to one another and/or to a reference point on the docking station such that a docking path to the base station can be determined from one or more observations of the at least two pose-defining fiducial markers. A mobile robot in the system has a chassis, a motorized drive connected to the chassis for moving the mobile robot to a docked position, and a pose sensor assembly having a sensor that is configured to output a signal in response to the at least two pose-defining fiducial marks in a

pose sensor field of view. A controller is located on the chassis and is configured to analyze the output signal from the pose sensor assembly. The controller has the predetermined spatial relationship of the pose-defining fiducial marker stored in a controller memory. The controller is configured to determine a docking station pose that is based on the spatial relationship of the pose-defining fiducial markers and the signals from the pose sensor assembly. The controller is further configured to locate the docking station pose on a map of a surface traversed by the mobile robot and to path plan a docking trajectory including a curve having a terminal portion aligned with a docking lane of the docking station, based on a current robot position on the map of the surface and the docking station pose and to provide instructions to the motorized drive to move the mobile robot along the curve of the docking trajectory and into a docking lane aligned with the docking station.

Ex1006, 1:26-55.

371. Fong discloses that the fiduciary markers allow a robot to return to its starting position. Ex1006, 1:26-55. Fong further discloses that the markers have a constrained relationship to all the nodes in the environment, including the docking station. Ex1006, 3:11-51. Specifically:

In some embodiments, or in the invention, a mobile robot system is provided that includes a docking station having at least two pose-defining fiducial markers. The pose-defining fiducial markers have a predetermined spatial relationship with respect to one another and/or to a reference point on the docking station such that a docking path to the base station can be determined from one or more observations of the at least two pose-defining fiducial markers. A mobile robot in the system has a chassis, a motorized drive connected to the chassis for moving the mobile robot to a docked position, and a pose sensor assembly having a sensor that is configured to output a signal in response to the at least two pose-defining fiducial marks in a pose sensor field of view. A controller is located on the chassis and is configured to analyze the output signal from the pose sensor assembly. The

controller has the predetermined spatial relationship of the pose-defining fiducial marker stored in a controller memory. The controller is configured to determine a docking station pose that is based on the spatial relationship of the pose-defining fiducial markers and the signals from the pose sensor assembly. The controller is further configured to locate the docking station pose on a map of a surface traversed by the mobile robot and to path plan a docking trajectory including a curve or pathway having a terminal portion aligned with a docking lane of the docking station, based on a current robot position on the map of the surface and the docking station pose and to provide instructions to the motorized drive to move the mobile robot along the curve of the docking trajectory and into a docking lane aligned with the docking station.

Ex1006, 3:11-51. As such, the robot can map out a path to ensure it returns to the docking station (same point). Ex1006, 4:45-5:8, 6:64-7:6.

372. It is also my opinion that it would have been obvious to a POSITA to combine Olson or Stachniss with Fong. Either Olson or Stachniss would give Fong the ability to locate the home locator, while Fong's home locator would help each of Either Olson or Stachniss reduce uncertainty. In fact, Fong specifically identifies using SLAM techniques, such as the ones disclosed in each of Olson and Stachniss, to help locate and map a starting location. Ex1006, 8:24-40. A POSITA would also have had a reasonable expectation of success in combining Olson or Stachniss with Fong because all the references refer to having an identifiable starting location as a reference point in the environment.

373. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

- f) **Claim 12: wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.**

374. 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 “wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.”

375. Fong explicitly discloses:

According to some embodiments, or in the invention, the service operation system **242** includes a floor cleaning system that cleans a floor surface of the enclosure space **20** as the robot **200** transits through the space **20**. In some embodiments, or in the invention, the service operation system **242** includes a suction head and an onboard vacuum generator to vacuum clean the floor. In some embodiments, or in the invention, the system **242** includes a sweeping or mopping mechanism.

Ex1006, 5:48-56. In addition, Fong discloses that a robot can be programed to clean certain rooms or multiple rooms. Ex1006, 6:37-7:6.

376. 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 the

SLAM techniques disclosed in each of Olson and Stachniss can be implemented in the robot in Fong because a cleaning robot would benefit from being able to know its location, and what was required of it in that location. As explained with respect to Element 1[b][3] (Section VII.C.2.c), Fong's robot could be programmed to have different functions in different locations. Ex1006, 6:64-7:2. This would not have been possible without the robot being able to map a large space and to tell the difference between various locations. A POSITA would also have had a reasonable expectation of success because Fong explicitly mentions SLAM (Ex1006, 8:24-50) as a way of performing this feature, and because it was routine for robots to conduct a specific function based on a location.

377. Therefore, it is my opinion that Olson in view of Fong or Stachniss in view of Fong discloses this limitation.

g) Element 13[c]: associating actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.

378. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

379. This limitation was addressed in the discussion of Element 1[b][3], and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* § VII.C.2.(c).

h) Claim 17: determining the robot returned to a start position based on detecting a home locator in the environment.

380. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

381. This limitation was addressed in the discussion of Claim 5, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* § VII.C.2.d.

i) Claim 18: limiting uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.

382. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

383. This limitation was addressed in the discussion of Claim 6, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* § VII.C.2.e.

384.

j) Claim 24: actuating one or more systems selectively as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.

385. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

386. This limitation was addressed in the discussion of Claim 12, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* § VII.C.2.f.

- k) **Element 25[pre]: A non-transitory computer readable medium comprising computer readable instructions stored thereon that when executed by at least one processing device configure the at least one processing device to,**

387. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

388. This limitation was addressed in the discussion of Elements 1(a)–(b), and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* §§ VII.C.2.a-b.

- l) **Element 25[c]: associate actions undertaken by the robot during traveling along the route with the location and position of the robot on the route on the map.**

389. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

390. This limitation was addressed in the discussion of Elements 1[b][3] and 13[c], and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* §§ VII.C.2.c, g.

- m) **Claim 29: wherein the at least one processing device is further configurable to execute the computer readable instructions to, determine the robot has**

returned to a start position based on detecting a home locator in the environment.

391. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

392. This limitation was addressed in the discussion of Claims 5 and 17, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* §§ VII.C.2.d, h.

- n) Claim 30: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, limit uncertainty of positioning of the plurality of nodes along the route traveled by the robot based on constraining start and end positions of the robot at a same point.**

393. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

394. This limitation was addressed in the discussion of Claims 6 and 18, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* §§ VII.C.2.e, i.

- o) Claim 36: wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels the route, the one or more systems comprises a cleaning system, the**

cleaning system comprises one or more of water flow, brush, and vacuum cleaner.

395. In my opinion, either Olson or Stachniss alone or in view of Fong discloses this limitation.

396. This limitation was addressed in the discussion of Claims 12 and 24, and it is disclosed in Olson/Stachniss alone or in view of Fong for substantially the same reasons. *See* §§ VII.C.2.f, j.

D. Ground 5: Claims 1–36 are Obvious Over Stachniss in combination with Prassler

397. It is my opinion that to the extent that Stachniss does not disclose claims 1–36, then it would have been obvious to combine Stachniss with Prassler to render each claim obvious.

1. Motivation to Combine Stachniss with Prassler

398. A POSITA would have been motivated to combine the domestic robots of Prassler and their functions, including its cleaning robots and functions, with the SLAM methods described in Stachniss. Prassler expressly teaches that cleaning robots may advantageously use SLAM techniques to efficiently and thoroughly clean surfaces. Ex1007, 1736, 1749–54. Prassler further teaches that customers want robots capable of efficient and thorough cleaning. Ex1007, 1734. A POSITA reading Prassler would have therefore been motivated to look for references disclosing SLAM methods. Stachniss discloses such methods in the very same volume. A POSITA interested in investigating SLAM methods to combine with

robots like those disclosed in Prassler would have naturally looked to the disclosure in Stachniss.

399. A POSITA reading Prassler and Stachniss would have had a reasonable expectation of success in such a combination. Prassler expressly teaches that others had combined SLAM techniques with cleaning robots and functions. Ex1007, 1733–36. Moreover, Prassler teaches that others had done so economically. Ex1007, 1736.

2. Element-by-element analysis

- a) **Claim 12: The system of claim 1, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.**

400. In my opinion, Stachniss alone or in view of Prassler renders this limitation obvious.

401. Prassler discloses autonomous domestic robots, including cleaning robots, with the claimed features. Ex1007, 1730–40. As discussed in Section VI.B.4 *supra* (incorporated here in its entirety), Prassler explains that floor cleaning robots have been known since 1985, and that low-cost robots with advanced mapping, route following, and sensor capabilities have been in known since 2008. Ex1007, 1730–

37; see § VI.B.4. Prassler presents a selection of robots that provided “[s]ystematic cleaning at low-cost” in Table 65.2 (reproduced below).

Table 65.2 Systematic cleaning at low-cost. The information in this table was partly collected from the websites and the technical documentation of the manufactures and partly from public websites such as www.botroom.com, staubsaugerroboter-test.org, www.robotreviews.com, www.geek.com, gizmodo.com, www.engadget.com

					
Manufacturer	LG	Samsung	Neato Robotics	Iclebo	Evolution Robotics/iRobot
Distributor			Vorwerk	Philips	Dirt Devil EVO/iRobot
Model	Hom-Bot 3.0	Navibot SR 8895 Silencio	Neato XV-21	Philips FC9910/01 HomeRun/ iclebo smart	Mint 4200
CPU	32 bit	2 CPUs			ARM7
Drive	Differential	Differential	Differential	Differential	Differential
Sensors	Camera (ceiling), camera (floor), sonar & infrared for collision avoidance cliff sensors, gyroscope, acceleration	Range sensors camera, cliff sensors, collision sensors, gyro	1-D laser range finder, cliff sensor, gyroscope, acceleration,	Camera (ceiling), cliff sensor, infrared for collision detection, gyroscope,	Northstar Indoor GPS, cliff sensors, bumper, gyro
Mapping and localization	SLAM	SLAM based on ceiling pictures at 30 fps (Visionary Mapping System)	SLAM based on laser range finder (onboard Room Positioning System (RPS))	SLAM based on ceiling pictures	SLAM with North- star, map-building
Navigation/coverage Cleaning technology	Systematic Brush roller, 2 side brushes	Systematic Brush roller, 2 side brushes	Systematic Bristled brush	Systematic Brush roller, 2 side brushes, micro-fiber mop	Systematic Dry or wet (or pre- moistened) microfiber cloths
Run time (min)	75	90	90	70	180
Performance	–	80 m ² /h	–	40 m ² /h	–
Docking/recharging station	Yes	Yes	Yes	Yes	No
Size (Ø/h) (cm)/(cm)	36/9	35/8	34× 34/10	35/10	31× 11/ 29
Weight (kg)	3,2	3,2	5	4	2
Year of launch	2011	2011	2012	2011	2010
Price range	US\$ 799.00 (Amazon.com)	EUR 349.00 (Amazon.de)	US\$ 350.00 (Amazon.com)	EUR 499.00 (Amazon.de)	US\$ 174.00 (Amazon.com)

Ex1007, Table 65.2.

402. Prassler discloses that domestic cleaning robots had at least one processing device configurable to execute computer readable instructions. For example, Prassler explains:

Let's say that you want to develop *a floor-care robot* that would retail at \$ 300, the rule of thumb is that your bill of materials (BOM) should be between 1/3–1/5 of the retail price. In other words, your BOM should be within \$ 60–\$ 100! And the BOM must include all mechanical parts, electrical parts, battery, *processor*, *memory*, motors, assembly, packaging, user manuals, etc.

Ex1007, 1747.

403. A POSITA would have understood that disclosure of a processor and memory as vital to a floor-care robot discloses at least one processing device configurable to execute computer readable instructions.

404. Prassler discloses that domestic cleaning robots included cleaning capabilities, including brushes, vacuum pumps, and water flow. Floor cleaners, for example, had brushes and vacuum pumps. Ex1007, 1730–36; *see, e.g.*, Ex1007, 1733 (including Table 65.1, listing the Sharper Image eVac with “Rotating brushes, vacuum pump”), 1734 (“The vacuum technology consists of a rotating brush, sometimes combined with a small fan [vacuum pump].”), 1736 (including Table 65.2, listing several vacuums with brush rollers, and side brushes). As a further example, automated pool cleaners included “cleaning technology” consisting of a “water pump and the filter to keep back the debris,” and “a system of counter-rotating rubber brushes which brush the debris underneath the pool cleaner, where it ends up in the intake socket of the water pump.” Ex1007, 1740.

405. Prassler further discloses that functions may be selectively actuated as the robot travels a route. For example, Prassler explains that “[t]he systematic robots

on the other hand take advantage of the localization system to plan efficient cleaning paths to maximize coverage in the least amount of time, *pause for charging* on the coking station and *resume cleaning from the last cleaned spot.*” Ex1007, 1754. Thus, Prassler discloses that these systems plan routes that involve deactivation of cleaning functions once they have achieved complete coverage of an area at a pre-determined point, at which point the robot continues along the route to return to the charging station. Ex1007, 1754. And Prassler further discloses that these systems also plan routes where they move from the charging station to a point in the map where the robot ceased cleaning on a prior mission, then activate cleaning functions at that point before proceeding along the remainder of the route. Ex1007, 1754.

406. It would have been obvious to combine the methods disclosed in Stachniss with the cleaning functions and selective activation in Prassler. Indeed, Prassler explicitly instructs that customers want systematic coverage and efficiency (Ex1007, 1734), and that such coverage and efficiency may be accomplished using SLAM methods (Ex1007, 1736, 1749–54). Prassler further explicitly instructs that selective activation “take[s] advantage of the localization system,” including SLAM methods. Ex1007, 1754. A POSITA reviewing Prassler would therefore have been motivated to combine the functions it discloses with SLAM methods, including those disclosed in Stachniss, contained within the very same volume. A POSITA reviewing Prassler would also have had a reasonable expectation of success, as

Prassler explains that others had already successfully combined these functions with SLAM to enable low-cost consumer-grade solutions. Ex1007, 1733–37.

- b) Claim 24: The method of claim 13, further comprising: actuating one or more systems selectively as the robot travels along the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.**

407. In my opinion, Stachniss alone or in view of Prassler renders this limitation obvious.

408. This limitation was addressed in the discussion of Claim 12, and it is rendered obvious by Stachniss alone or in view of Prassler for substantially the same reasons. *See* § VII.D.2.a.

- c) Claim 36: The non-transitory computer readable medium of claim 25, wherein the at least one processing device is further configurable to execute the computer readable instructions to, selectively actuate one or more systems as the robot travels the route, the one or more systems comprises a cleaning system, the cleaning system comprises one or more of water flow, brush, and vacuum cleaner.**

409. In my opinion, Stachniss alone or in view of Prassler renders this limitation obvious.

410. This limitation was addressed in the discussion of Claims 12 and 24, and it is rendered obvious by Stachniss alone or in view of Prassler for substantially the same reasons. *See* §§ VII.D.2.a, b.

VIII. SECONDARY CONSIDERATIONS

411. 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 '576 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.

412. 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.

413. 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

414. 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.

415. For the reasons set forth above, it is my opinion that the Challenged Claims of the '576 patent are invalid.

Executed on November 5, 2025
Scottsdale, Arizona

By: 

Dr. Lina J. Karam