Recent advances on simultaneous localization and mapping for mobile robots

Article *in* IETE Technical Review · November 2013

DOI: 10.4103/0256-4602.125671

2 authors:

Erik Zamora
Instituto Politécnico Nacional

Wen Yu
Center for Research and Advanced Studies of the National Polytechnic Institute

Recent Advances on Simultaneous Localization and Mapping for Mobile Robots

Erik Zamora and Wen Yu

Department of Automatic Control, CINVESTAV-IPN, Mexico City, Mexico

Abstract

This paper gives recent advances made in simultaneous localization and mapping (SLAM) in the last decade. It summarizes the main contributions, insights, limitations, and solutions of the most popular SLAMs. Some important approaches that cannot be included in the above classifications are also discussed, such as pedestrian SLAM, SLAM with enriched maps, multi-robot SLAM, active SLAM, and SLAM in dynamic environments.

Keywords

Simultaneous localization and mapping, Mobile robots, Various SLAM.

1. Introduction

The objective of the simultaneous localization and mapping (SLAM) is to localize the robot from any initial location and create a model of the unknown environment at the same time. The SLAM is a chicken-and-egg problem because the robot needs a map to localize itself and the map needs exact localization of robot to create a consistent map. Therefore, the solution of SLAM must be recursive. We classify the solutions into the following four classes:

(1) Feature-based SLAM: It is the most popular approach to solve the SLAM problem. It uses predefined landmarks and environment model to estimate the robot current state (or robot path) and the map [1]. There are four different techniques to the state estimation [2]: extended Kalman filter (EKF), information extended filter (IEF), particles filter (PF), and optimization techniques (graph based) [3].

状态估计有四种不同的技术

(2) Pose-based SLAM: Only the robot state trajectory is estimated, without landmark positions. The robot path is estimated using constraints imposed by the landmark positions or the raw laser (or visual) data. Similar to the feature-based SLAM, the path estimation also can be performed by optimization techniques [4], information [5], and particles filtering methods [6].

(3) Appearance-based SLAM: It does not use metric information and the landmark positions. The robot path is not tracked in metric sense. The visual images or spatial information are utilized to recognize the place. It is very common that these appearance techniques are used complementary to any metric SLAM method to detect loop closures [7].

(4) There are several variants in SLAM problem that cannot be included in the above paradigms. Pedestrian SLAM employs light and cheap sensors, and faces the obstacle of human movements which are different to robot behavior [8]. SLAM with enriched maps uses auxiliary information, such as humanity, temperature, terrain characteristics, and meanings, in the map [9]. Active SLAM derives a control law for robot navigation in order to achieve efficiently a certain desired accuracy of the robot location and the map [10]. Multi-robot SLAM uses many robots for large environment [11]. SLAM in dynamic environment or at least non-static environments deals with moving objects and agents.

Some reviews have been published on SLAM since 2002. In the work of Thrun [12], a comparison of probabilistic techniques on robotic mapping was provided. Frese [13] compared nine SLAM algorithms for feature- and pose-based SLAM and discussed the structure and properties of SLAM problem. Durrant-Whyte *et al.* in their tutorial papers [14,15] described the probabilistic structure, complexity, and environment modeling of SLAM problem, and presented EKF and FastSLAM methods. Lu *et al.* [16] reviewed the sensor problem in SLAM. Dissanyake *et al.* [17] discussed the properties of SLAM, such as observability, convergence, consistency, computational complexity, and optimization convexity.

Many improvements have been made in recent years. A complete review on the recent advances of SLAM is needed. In this paper, the summarization of the most important insights, limitations, and solutions of SLAM are emphasized. After the discussion of the properties of SLAM, most types of SLAM are reviewed.

2. Feature SLAM Solutions

In this section, we present some feature SLAM solutions and their properties, classifying them by the state estimation technique.

2.1 Kalman Filter SLAM

Kalman filter SLAM (EKF-SLAM) is the first solution for the online SLAM problem. The complete discussion can be found in [1]. The Kalman filter SLAM represents the robot and environment in a state space model with the Gaussian noise. The estimated state includes the position and orientation of the robot and the position of all landmarks.

Since the Gaussian noise assumption is not realistic and causes fake landmarks in the map, EKF-SLAM requires additional techniques to manage the map to eliminate the fake landmarks. The consistency and convergence of the EKF-SLAM algorithm are presented in [18]. Rodriguez-Lasada *et al*.[19] reviewed various techniques to overcome the inconsistency problem of EKF-SLAM. The biggest disadvantage of EKF-SLAM is that its computing time is quadratic over the number of landmarks due to the update of the covariance matrix. There are several ways to overcome this limitation. They are as follows:

EKF - SLAM最大的缺点是由于协方差矩阵的更新，其计算时间是地标数的二次

(1) Limiting the number of landmarks to be estimated [2].
(2) Updating only the part of currently detected landmarks and postponing the complete update in later time [20].
(3) Making approximations in the covariance update stage [21].
(4) Assuming that most main lines in the environment are parallel or perpendicular [22].

On the other hand, there have been proposals to use other Kalman filtering techniques to further enhance the accuracy and improve the robustness of the divergence, e.g. using unscented Kalman Filter [23] and cubature Kalman Filter [24].

2.2 Information-based SLAM

Motivated by reducing the complexity of EKF-SLAM in larger environments, the extended information filter (EIF) was developed to replace EKF. The great advantage of EIF over EKF is that the time complexity can be reduced due to the sparseness property of the information matrix. However, the recovery of the landmark positions and the covariances associated with the landmarks in the vicinity of the robot is needed for data association, map update, and robot localization. When the number of landmarks is small, it can be obtained by the inverse of the information matrix, but the computational cost of the inversion will be unacceptable with a large information matrix. We describe various approaches using the information matrix approach.

我们使用信息矩阵方法描述各种方法

利用稀疏特性

SEIF-SLAM: The sparse extended information filter (SEIF) algorithm was developed by Thrun *et al*. [25]. The key property is that even if the covariance matrix is dense, the normalized information matrix tends to be almost sparse. By sparse property, the measurement and motion updates are realized in a constant time interval. They proposed an amortized constant-time hill climbing algorithm to recover the vector mean from the information matrix. The maximum likelihood approach for data associations was modified to associate the landmarks and measurements in constant time. The disadvantages of SEIF are overconfidence and map inconsistency, i.e., the covariance matrix may suggest a higher degree of confidence than actually warranted by the sensor measurements. A detail discussion on the inconsistency due to the sparseness approximation was developed by Eustice *et al*. [26].

ESEIF-SLAM: In order to avoid the overconfidence problem of SEIF, Walter *et al*. [27] proposed the exactly sparse extended information filter (ESEIF). It produced exact sparseness of the matrix information. Rather than breaking constraints to maintain sparsity, ESEIF controls the initial formation of links and the number of active landmarks by deliberately marginalizing out the robot pose. The robot is relocated within the map using observations of a few known landmarks. The robot is linked only to the features used for re-localization, preserving the sparsity of matrix information.

D-SLAM: The decoupled SLAM (D-SLAM) proposed by Wang *et al*. [28] used relative maps together with EIF to divide the SLAM problem into global landmarks estimation, and robot and local landmarks estimation. It results in an exact sparse information matrix for mapping, without enforcing the sparsity even during loop closure events. Thus, the D-SLAM algorithm does not contain any approximations that can lead to inconsistency.

2.3 Graph-based SLAM

Graph-based SLAM methods use optimization techniques to transfer the SLAM problem into a nonlinear quadratic programming. The historical development of this paradigm has focused on pose-only approaches (Section 3) and using the landmark positions to obtain constraints for the robot path. The following methods use optimization techniques to estimate both the landmarks and robot states.

GraphSLAM: Montemerlo and Thrun [3] proposed the GraphSLAM algorithm to solve the full SLAM problem. GraphSLAM extracts a set of nonlinear constraints from measurements, and then linearizes and reduces them through variable elimination techniques. It uses least-square optimization to represent the information matrix. The GraphSLAM can be solved by the conjugate

基于信息矩阵的平滑技术

gradient descent method. The estimation accuracy is better than that of the other SLAM methods. However, the conjugate gradient in it is slow to be implemented in real time.

Square root SLAM: Dellaert and Kaess [29] used a smoothing technique based on information matrix. It is called square root smoothing and mapping (SAM) and it solves SLAM in batch or incremental mode. SEIF removes links of the information matrix to reduce the computational cost. In contrast, if the smoothing information matrix is naturally sparse, then the solution of SAM is exact. By using Cholesky and QR factorization, SAM estimates the robot poses and landmark positions with the least-square method. Kaess *et al.* [30] proposed an incremental version of SAM (iSAM) to improve the real-time performance.

Sliding window filter: Sibley *et al*. proposed a semi-recursive SLAM via nonlinear least-squares optimization and the sliding window filter (SWF). The state vector retains only the most recent robot poses and the closest landmarks, rather than the whole robot trajectory and all the landmarks. In order to maintain the vector state size bounded, they applied the Shur complement method to the least squares for marginalizing out the oldest robot poses and distant landmarks. The marginalized nonlinear least-squares problem is solved by Gauss–Newton method using the Huber kernel. Due to the marginalization, the time complexity is constant over the number of landmarks and the robot poses. It is feasible to run in real time. Another good property is that the size of the vector state can be controlled. Another good property is that the size of the vector state can be adjusted such that the useful resources are included.

2.4 Sub-mapping Techniques

In order to deal with time complexity and manage large environments, the map can be separated into a set of sub-maps. The difficulty lies in joining the sub-maps together. No matter how good the algorithm is, SLAM solution will inevitably need to split a very large environment to reduce the computational processing. There are several ways to discompose the map, which can be classified in the following two groups:

尺度地图由大到小分级

Metric–metric approach: It divides the whole map into smaller parts using a high-metric-level approach over the metric sub-maps, estimating the global locations of sub-map relative to a common frame. Some of the important proposals are as follows: (1) The divide and conquer SLAM (D and C SLAM) [31] joins maps in a hierarchical fashion. The time of building local maps is $O(1)$. It recovers the global map in linear time $O(N)$, where N is the number of landmarks. This performance gain is not obtained by sacrificing precision. (2) Huang *et al*. [32] presented a sub-map joining technique called sparse local sub-map joining filter (SLSJF). They used EIF to fuse sub-maps. In the worst case, the theoretical time complexity is $O(N^{1.5})$. (3) Cadena and Neira [33] proposed combined Kalman information filter (CKIF), a combination of EFK and EIF. They concluded that CKIF is faster than D and C SLAM and SLSJF, with the same accuracy. However, it is impossible for CKIF to recover the covariance efficiently in the data association.

有一个全局拓扑地图和各种局部度量子地图来表示环境

Topological–metric approaches: The idea is to have a global topological map and various local metric sub-maps for representing the environment. Some specific proposals are as follows: (1) Bosse *et al*. [34] applied Atlas framework, a hybrid metric/topological SLAM algorithm, to achieve mapping of large-scale environments, which is an indoor structured environment of 2.2 km path length with multiple loops. (2) Lisien *et al*. [35] proposed the hierarchical SLAM (HSLAM), where a topological map is decomposed into regions, within which the robot can build a local metric map of landmarks. The edges of the topological graph not only connect neighboring nodes but also define paths through the free space. (3) Frese [36] introduced the tree-map algorithm. The fundamental idea of the tree-map is to divide recursively the environment into binary tree. An advantage of the tree-map algorithm is that it is able to change the identity of landmarks already integrated into the map, making it more robust to data association errors.

2.5 PF SLAM

PF的主要缺点是在高维空间中采样计算效率低

Unlike Kalman filter and information filters, the PF is not bounded to unmodeled distribution. PF is a sequential Monte Carlo inference method that approximates the exact probability distribution through a set of state samples. The advantage over EKF and EIF is that PF can represent any multi-model probability distribution. It does not need Gaussian assumption. The main drawback of PF is that the sampling in a high-dimensional space is computational inefficient. But if the problem estimation has nice structure, we can reduce the size of the space using the Rao–Blackwellized Particles Filter (RBPF) which marginalizes out some of the random variables. There are two representative SLAM techniques using PF.

FastSLAM: The FastSLAM algorithm of Montemerlo *et al*. [37] is based on the fact that the landmarks are conditionally independent of each other if the robot pose is known. This fact allows applying the RBPF to estimate the robot path and to estimate the landmark position by several low-dimensional EKFs. The particles in FastSLAM represent a whole robot path history. The FastSLAM uses a binary tree to represent the set of landmarks, which allows to execute the updates in logarithmic time $O(M \log N)$, where M can be constant.

The advantages of the FastSLAM are: (1) the data association is multiple because each particle has a different

能更好地处理非线性和非高斯系统

view of the map, and thus is more robust to association errors; (2) it does not need linearization of robot's motion or measurement models; and (3) it can cope better with nonlinear and non-Gaussian systems. Its disadvantages are: (1) since the data association of the FastSLAM must be performed for each particle independently, the computational cost is expensive; (2) the FastSLAM has the problem of the susceptibility to divergence in sparse and noisy SLAM; (3) its consistency is always lost in the long term [38], although increasing the number of particles can prolong it. Finally, there are improved versions of the FastSLAM based on the filter modification. For example, the UFastSLAM algorithm [39] used unscented Kalman filter, and in [40], the cubature Kalman filter was used.

PHD-SLAM: The Gaussian mixture probability hypothesis density (PHD) filter was used for each map by Mullane *et al*. [41]. It represents the map as a random finite set (RFS) of landmarks. This allows using the tool of finite set statistics for error estimation between sets, instead of vectors. The RFS framework permits the integration of uncertainty in data association and the number of features into the same Bayesian filter, avoiding the use of a separate data association step or any form of landmark management [42]. The experimental results show that the PHD-SLAM algorithm is more accurate and more robust than FastSLAM.

基于姿态的slam和基于特征的slam的主要区别在于前者不估计地标位置。计算成本随机器人姿态数的增加而增加，且与地图大小无关

3. Pose-based SLAM Solutions

The main difference between the pose-based and feature-based SLAMs is that the former does not estimate the landmarks positions. The computation cost increases with the number of robot poses, and it is independent of the map size. Based on the state estimation method, the pose-based SLAM can be grouped into three types.

Graph-based SLAM: The constraints between the pose of the robot and the landmarks are represented by a graphical network [4]. A key assumption in the graph-based SLAM is that the noise is in Gaussian form as EKF-SLAM. This leads to a nice set of quadratic objective function which can be optimized. Although in the real world, this noise does not exist, the obtained maps have sufficiently good accuracy. Another assumption of the graph-based SLAM is static world. It is a great limitation in dynamic environments.

一个假设是噪声符合高斯分布；另一个假设是周围环境是静态的

The graph-based SLAMs do not use filtering techniques to estimate the environment states. Instead, they can be estimated by the following iterative and direct optimization methods:

(1) *Gradient descent*: Folkesson and Christensen[4] proposed a method to reduce the graph using star nodes, which divide the graph into some independent components to facilitate real-time operation.

(2) *Conjugate gradient*: To reduce the computational cost, Konolige [43] calculated the matrix inversion with preconditioned conjugate gradient method.

(3) *Stochastic gradient descent*: The main weakness of the gradient descent and the conjugate gradient is that they suffer from bad initial estimation of robot poses. Olson *et al*. [44] proposed the stochastic gradient descent method to jump from one local minimum to another one to search the global minimum. Grisetti *et al*. [45] applied a tree parameterization method to improve Olson's algorithm. They also used the node reduction technique and the adaptive learning rate to speed up the convergence.

(4) *Levenberg–Marquardt method*: Konolige *et al*. [46] used a modified Levenberg–Marquadt method and Cholesky decomposition solver for the sparse linear system. It is also called sparse pose adjustment. It is faster than the algorithm of Grisetti *et al*. [45], and less robust with respect to bad initialization.

它也被称为稀疏姿态调整　　比上述方法快，但是受初始值影响

To improve the online performance, some researchers used the hierarchical optimization schemes. Grisetti *et al*. [47] used the coarse structure of pose graph to maintain the essential information for the data associations. Kretzschmar *et al*. [48] proposed a pruning technique to deal with the computational cost related to the length of robot trajectory. Dellaert *et al*. [49] proposed sub-graph preconditioned conjugate gradients algorithm to batch the optimization methods. In order to prevent the divergence of optimization process due to data association errors, Sünderhauf and Protzel [50] reformulated the objective function, allowing the optimization process to change parts of the topological structure of the graph.

Information-based SLAM: The pose SLAM can use the information filter to estimate the robot poses. Eustice *et al*. [5] proposed the exactly sparse delayed-state filter to exploit the same sparse property to simplify the algorithm complexity. Ila *et al*. [51] introduced an information-based compact pose SLAM to reduce the computational cost by adding only highly informative loop-closure links and non-redundant poses to the robot path.

Particle-based SLAM: This SLAM uses particle filters to estimate the robot poses. In DP-SLAM of Eleazar and Parr [52], each particle corresponded to a specified trajectory of robot and had a specific map associated with it. The algorithm was based on laser scans and storing multiple maps. A grid version of FastSLAM was introduced in [6]. It used a scan matching for the pose estimation. An adaptive re-sampling technique was used to maintain a reasonable variety of particles.

4. Appearance-based SLAM Solutions

Instead of metric information, the appearance-based

SLAM uses the appearance information of the environment. We discuss here several approaches to recognize the places based on visual and spatial information of the environment and the methods of creating topological maps.

Visual appearance: The appearance-based SLAM does not use the tracks of the robots or the landmarks in metric coordinates. The map is constructed based on topological sense of the visited places. It can be used as an additional technique for the metric-based SLAM to detect the loop closure and the place. Similarity measurement is needed in the appearance-based SLAM to decide if a place has been visited, using for example, visual landmarks [53].

The most important appearance-based SLAM is the visual vocabulary approach. Fraundorfer *et al*. [54] built a topological map of visited places via a vocabulary tree. Schindler *et al*. [55] used information gain to build the vocabulary tree and to inhibit future matches from the same set of features. The biologically inspired SLAM [56] can also be regarded as a visual appearance-based algorithm. Newman *et al*. [57] proposed a fast appearance-based SLAM, which used a probabilistic framework based on Monte Carlo approximation. The time complexity is linear in a number of locations.

Unlike the above approaches, Angeli *et al*. [58] proposed an incremental method for loop closure detection, where the visual vocabulary construction is online along with the image acquisition. More recently, Nicosevici and Garcia [59] proposed a method called online visual vocabulary (OVV). They used Fisher's linear discriminant as the clustering criterion to increase the distance between clusters of images and their compactness, maximizing the repeatability and discriminative power of the vocabulary.

Finally, the appearance paradigm is fused with local odometric data. Maddern *et al*.[60] proposed the CAT-Graph method, which does not construct a global metric map. Instead, it maintains only relative local metric information between places, fused with appearance information employing a particle filter. Its navigation system demonstrates that global metric accuracy is not needed for navigation tasks and the persistent autonomous operation of a mobile robot is possible.

Spatial appearance: The spatial appearance SLAM uses the range data, rather than visual images, to detect the place and the loop closure. Usually it uses 2D laser range finders based on segment descriptors, orientation histograms, clusters of large positive curvature points, interest region transformation, etc., [61]. Recently, 3D range data were used to detect the loop closure and the place based on, for example, normal distributions transformation, normal-aligned radial features, and different other descriptors [62]: spin images, shape context, and moment grids.

Visual and spatial appearance: The combination of the visual and spatial information can improve robustness in recognizing the places, reduce perceptual aliasing, and improve the distinctiveness of places, e.g. Tapus [63] used the place fingerprints, which contain color patches, vertical edges, and the extremity of line segments, to detect the loop closure. More recently, Cadena *et al*. [64] employed conditional random fields to verify unclear loop closures based on both image and spatial information. The inference is carried out on minimum spanning tree to limit its computational cost.

Topological SLAM: Topological maps are attractive due to the reduced storage requirements. They are more scalable to deal with larger environments. In addition, they have good integration with motion planning algorithms and are also more intuitive for persons to give navigation indications. In this research line, Ranganathan *et al.* [65] developed an online probabilistic framework for inference in the space of topological maps, where the posterior topological map is updated incrementally.

Pedestrian SLAM: The SLAM community has been explored with pedestrian SLAM techniques [66-68]. The main problems are pedestrians have much more complex movements than any mobile robot and the intelligent selection of economic and light sensors [69-71].

SLAM in dynamic environments: The moving objects may cause data association errors, failure in landmark detection, failure in loop closing event, and consequently, divergence in state estimation [72,73].

5. Conclusion

In this paper, we have given a brief account of the most important SLAM paradigms. We have also presented some special cases for SLAM problems in dealing with dynamic environments, multi-robot interaction, active control, enriched maps, and for pedestrian applications.

References

1. S. Thrun, W. Burgard, and D. Fox, "Probabilistic Robotics," Kharagpur, Sri Lanka, 2005.
2. G. Dissanayake, S.B. Williams, H. Durrant-Whyte, and T. Bailey, "Map Management for Efficient Simultaneous Localization and Mapping (SLAM)", Journal of Autonomous Robots, Vol. 12, no. 3, pp. 267-86, 2002.
3. S. Thrun, and M. Montemerlo, "The GraphSLAM algorithm with applications to large-scale mapping of urban structures", International Journal on Robotics Research, Vol. 25, no. 5, pp. 403-29, 2006.

4. J. Folkesson, and H. Christensen, "Closing the Loop With Graphical SLAM", IEEE Transactions on Robotics, Vol. 23, no. 4, pp. 731-41, 2007.

5. R.M. Eustice, H. Singh, and J.J. Leonard, "Exactly Sparse Delayed-State Filters for View-Based SLAM", IEEE Transactions on Robotics, Vol. 22, no. 6, pp. 1100-14, 2006.

6. G. Grisetti, C. Stachniss, and W. Burgard, "Improved Techniques for Grid Mapping With Rao-Blackwellized Particle Filters", IEEE Transactions on Robotics, Vol. 23, no. 1, pp. 34-46, 2007.

7. K.L. Ho, and P. Newman, "Loop closure detection in SLAM by combining visual and spatial appearance", Robotics and Autonomous Systems, Vol. 54, no. 9, pp. 740-9, 2006.

8. H. El Mokni, and F. Govaers, "Coupled laser inertial navigation system for pedestrian tracking", in 8th Workshop on Positioning Navigation and Communication, pp. 176-9, 2011.

9. J. Nieto, J. Guivant, and E. Nebot, "DenseSLAM: Simultaneous Localization and Dense Mapping", The International Journal of Robotics Research, Vol. 25, pp. 711-44, 2006.

10. T. Kollar, and N. Roy, "Trajectory Optimization using Reinforcement Learning for Map Exploration," International Journal of Robotics Research, Vol. 27, no. 2, pp. 175-96, 2008.

11. D. Fox, J. Ko, K. Konolige, B. Limketkai, D. Schulz, and B. Stewart, "Distributed Multirobot Exploration and Mapping", Proceedings of the IEEE, Vol. 94, no. 7, pp. 1325-39, 2006.

12. S. Thrun, "Robotic Mapping: A Survey", in Exploring Artificial Intelligence in the New Millennium, The Morgan Kaufmann Series in Artificial Intelligence, 2002.

13. U. Frese, "A Discussion of Simultaneous Localization and Mapping", Autnomous Robots, Vol. 20, no. 1, pp. 25-42, 2006.

14. H. Durrant-Whyte, and T. Bailey, "Simultaneous localization and Mappping (SLAM): Part I The essential algorithms", IEEE Robotics and Automation Magazine, Vol. 13, no. 2, pp. 99-110, 2006.

15. T. Bailey, and H. Durrant-Whyte, "Simultaneous localization and mapping (SLAM): part II", IEEE Robotics and Automation Magazine, Vol. 13, no. 3, pp. 108-17, 2006.

16. Z. Lu, Z. Hu, and K. Uchimura, "SLAM Estimation in Dynamic Outdoor Environments: A Review", in Intelligent Robotics and Applications, Lecture Notes in Computer Science (5928), pp. 255-67, 2009.

17. G. Dissanayake, S. Huang, Z. Wang, and R. Ranasinghe, "A review of recent developments in Simultaneous Localization and Mapping", in 6th IEEE International Conference on Industrial and Information Systems, pp. 477-82, 2011.

18. S. Huang, and G. Dissanayake, "Convergence and Consistency Analysis for Extended Kalman Filter Based SLAM", IEEE Transactions on Robotics, Vol. 23, no. 5, pp. 1036-49, 2007.

19. D. Rodriguez-Losada, F. Matia, A. Jimenez, and R. Galan, "Consistency improvement for SLAM - EKF for indoor environments", in IEEE International Conference on Robotics and Automation, pp. 418-23, 2006.

20. E.D. Nerurkar, and S.I. Roumeliotis, "Power-SLAM: A linear-complexity, anytime algorithm for SLAM", International Journal of Robotics Research, Vol. 30, no. 3, pp. 772-88, 2011.

21. S. Julier, and J. Uhlmann, "Using covariance intersection for SLAM", Robotics and Autonomous Systems, Vol. 55, no. 1, pp. 3-20, 2007.

22. V. Nguyen, A. Harati, A. Martinelli, R. Siegwart, and N. Tomatis, "Orthogonal SLAM: a Step toward Lightweight Indoor Autonomous Navigation", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5007-12, 2006.

23. R. Martinez-Cantin, and J.A. Castellanos, "Unscented SLAM for large-scale outdoor environments", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3427-32, 2005.

24. K. Pakki, B. Chandra, Da-Wei Gu, and I. Postlethwaite, "Cubature Kalman Filter based Localization and Mapping", in 18th IFAC World Congress, Milano, Italy, 2011.

25. S. Thrun, Y. Liu, D. Koller, A.Y. Ng, Z. Ghahramani, and H. Durrant-Whyte, "Simultaneous Localization and Mapping with Sparse Extended Information Filters", International Journal of Robotics Research, Vol. 23, no. 3, pp. 693-16, 2004.

26. R. Eustice, M. Walter, and J. Leonard, "Sparse extended information filters: Insights into sparsification", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3281-8, 2005.

27. M. Walter, R. Eustice, and J. Leonard, "A provably consistent method for imposing sparsity in feature-based SLAM information filters", in International Symposium of Robotics Research, pp. 214-234, 2005.

28. Z. Wang, S. Huang, and G. Dissanayake, "D-SLAM: A Decoupled Solution to Simultaneous Localization and Mapping", International. Journal of Robotics Research, Vol. 26, no. 2, pp. 187-204, 2007.

29. F. Dellaert, and M. Kaess, "Square Root SAM: Simultaneous Localization and Mapping via Square Root Information Smoothing", International Journal of Robotics Research, Vol. 25, pp. 1181-203, 2006.

30. M. Kaess, H. Johannsson, R. Roberts, V. Ila, J. Leonard, and F. Dellaert, "iSAM2: Incremental smoothing and mapping using the Bayes tree", International Journal of Robotics Research, Vol. 31, pp. 216-35, 2012.

31. L.M. Paz, J.D. Tardós, and J. Neira, "Divide and Conquer: EKF SLAM in," IEEE Transactions on Robotics, Vol. 24, no. 5, pp. 1107-20, 2008.

32. S. Huang, Z. Wang, and G. Dissanayake, "Sparse Local Submap Joining Filter for Building Large-Scale Maps", IEEE Transactions on Robotics, Vol. 24, no. 5, pp. 1121-30, 2008.

33. C. Cadena, and J. Neira, "SLAM in O (log n) with the Combined Kalman - Information filter", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 2069-76, 2009.

34. M. Bosse, P. Newman, J. Leonard, and S. Teller, "Simultaneous Localization and Map Building in Large-Scale Cyclic Environments Using the Atlas Framework", International Journal of Robotics, Vol. 23, pp. 1113-39, 2004.

35. B. Lisien, D. Morales, D. Silver, G.A. Kantor, I. Rekleitis, and H. Choset, "The hierarchical atlas", IEEE Transactions on Robotics, Vol. 21, no. 3, pp. 473-81, 2005.

36. U. Frese, "Efficient 6-DOF SLAM with Treemap as a Generic Backend", in IEEE International Conference on Robotics and Automation, pp. 4814-9, 2007.

37. M. Montemerlo, and S. Thrun, "FastSLAM, A Scalable Method for the Simultaneous Localization and Mapping Problem in Robotics", Springer; 2007.

38. T. Bailey, J. Nieto, and E. Nebot, Consistency of the FastSLAM algorithm, in IEEE Int. Conf. Robot. Autom., pp. 424-9, 2006.

39. C. Kim, R. Sakthivel, and W.K. Chung, "Unscented FastSLAM: A Robust and Efficient Solution to the SLAM Problem", IEEE Transactions on Robotics, Vol. 24, no. 4, pp. 808-20, 2008.

40. Y. Song, Q. Li, Y. Kang, and Y. Song, "CFastSLAM: A new Jacobian free solution to SLAM problem", in IEEE International Conference on Robotics and Automatio, pp. 3063-8, 2012.

41. J. Mullane, B.N. Vo, M. Adams, and B.T. Vo, "A Random-Finite-Set Approach to Bayesian SLAM", IEEE Transactions on Robotics, Vol. 27, no. 2, pp. 268-82, 2011.

42. G. Sibley, L. Matthies, and G. Sukhatme, Sliding window filter with application to planetary landing, Journal of Field Robotics, Vol. 27, no. 5, pp. 587-608, 2010.

43. K. Konolige, "Large-scale map-making," in 19th national conference on Artifical Intelligence, pp. 457-63, 2004.

44. E. Olson, J. Leonard, and S. Teller, Fast iterative optimization of pose graphs with poor initial estimates, in IEEE ICRA, pp. 2262-9, 2006.

45. G. Grisetti, R. Kümmerle, C. Stachniss, and W. Burgard, "A Tutorial on Graph-Based SLAM", IEEE Intelligent Transportation Systems Magazine, Vol. 2, no. 4, pp. 31-43, 2010.

46. K. Konolige, G. Grisetti, R. Kümmerle, W. Burgard, B. Limketkai, and R. Vincent, "Efficient Sparse Pose Adjustment for 2D mapping", in IEEE/RSJ International Conference on Intelligent

Robots and Systems, pp. 22-9, 2010.

47. G. Grisetti, R. Kummerle, C. Stachniss, U. Frese, and C. Hertzberg, "Hierarchical optimization on manifolds for online 2D and 3D mapping", in IEEE International Conference on Robotics and Automation, pp. 273-8, 2010.

48. H. Kretzschmar, C. Stachniss, and G. Grisetti, "Efficient information-theoretic graph pruning for graph-based SLAM with laser range finders", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 865-71, 2011.

49. F. Dellaert, J. Carlson, V. Ila, K. Ni, and C. Thorpe, "Subgraph-preconditioned conjugate gradients for large scale SLAM", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 2566-71, 2010.

50. N. Sunderhauf, and P. Protzel, "Towards a robust back-end for pose graph SLAM", in IEEE International Conference on Robotics and Automation, pp. 1254-61, 2012.

51. V. Ila, J.M. Porta, and J. Andrade-Cetto, "Information-Based Compact Pose SLAM", IEEE Transactions on Robotics, Vol. 26, no. 1, pp. 78-93, 2010.

52. A. Eliazar, and R. Parr, "DP-SLAM 2.0", in IEEE International Conference on Robotics and Automation, pp. 1314-20, 2004.

53. K Sharma, I. Moon, and S.G. Kim, "Extraction of Visual Landmarks Using Improved Feature Matching Technique for Stereo Vision Applications", IETE Tech Rev, Vol. 29, pp. 473-81, 2012.

54. F. Fraundorfer, C. Engels, and D. Nister, "Topological mapping, localization and navigation using image collections", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3872-7, 2007.

55. G. Schindler, M. Brown, and R. Szeliski, "City-Scale Location Recognition", in IEEE Conference on Computer Vision and Pattern Recognition, pp. 1-7, 2007.

56. M. Milford, and G. Wyeth, "Persistent Navigation and Mapping using a Biologically Inspired SLAM System", International Journal of Robotics. Research, Vol. 29, no. 9, pp. 1131-53, 2010.

57. M. Cummins, and P. Newman, "Accelerating FAB-MAP with concentration inequalities", IEEE Transactions on Robotics, Vol. 26, no. 6, pp. 1042-50, 2010.

58. A. Angeli, D. Filliat, S. Doncieux, and J.A. Meyer, "Fast and Incremental Method for Loop-Closure Detection Using Bags of Visual Words", IEEE Transactions on Robotics, Vol. 24, no. 5, pp. 1027-37, 2008.

59. T. Nicosevici, and R. Garcia, "Automatic Visual Bag-of-Words for Online Robot Navigation and Mapping", IEEE Transactions on Robotics, Vol. 28, no. 4, pp. 886-98, 2012.

60. W. Maddern, M. Milford, and G. Wyeth, "Towards persistent indoor appearance-based localization, mapping and navigation using CAT-Graph", in IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 4224-30, 2012.

61. K. Granström, J. Callmer, F. Ramos, and J. Nieto, "Learning to detect loop closure from range data", in IEEE Int. Conf. on Robotics and Automation, pp. 15-22, 2009.

62. M. Bosse, and R. Zlot, "Place recognition using regional point descriptors for 3D mapping", in Field and Service Robotics, pp. 195-204, 2010.

63. A. Tapus, "Topological SLAM-Simultaneous Localization and Mapping with Fingerprints of Places", PhD Thesis, École Polytechnique Fédérale de Lausanne, 2005.

64. C. Cadena, D. Galvez-Lopez, J.D. Tardos, and J. Neira, "Robust Place Recognition With Stereo Sequences", IEEE Transactions on Robotics, Vol. 28, no. 4, pp. 871-85, 2012.

65. A. Ranganathan, and F. Dellaert, "Online probabilistic topological mapping", International Journal of Robotics Research, Vol. 30, pp. 755-71, 2011.

66. S. Grzonka, A. Karwath, F. Dijoux, and W. Burgard, "Activity-Based Estimation of Human Trajectories", IEEE Transactions on Robotics, Vol. 28, no. 1, pp. 234-45, 2012.

67. M. Angermann, and P. Robertson, "FootSLAM: Pedestrian Simultaneous Localization and Mapping Without Exteroceptive Sensors – Hitchhiking on Human Perception and Cognition", in Proceedings of the IEEE, pp. 1840-8, 2012.

68. H. Shin, Y. Chon, and H. Cha, "Unsupervised Construction of an Indoor Floor Plan Using a Smartphone", IEEE Transactions on Systems, Man, and Cybernetics, Part C, Vol. 99, pp. 1-10, 2011.

69. D.F. Wolf, and G.S. Sukhatme "Semantic Mapping Using Mobile Robots", IEEE Transactions on Robotics, Vol. 24, no. 2, pp. 245-58, 2008.

70. J.S. Lee, C. Kim, and W.K. Chung, "Robust RBPF-SLAM using sonar sensors in non-static environments", in IEEE International Conference on Robotics and Automation, pp. 250-6, 2010.

71. C.C. Wang, C. Thorpe, S. Thrun, M. Hebert, and H. Durrant-Whyte, "Simultaneous Localization, Mapping and Moving Object Tracking", International Journal of Robotics Research, Vol. 26, pp. 889-916, 2007.

72. D.Guan, T. Ma, W. Yuan, Y.K. Lee, and A.M. Jehad, "Review of Sensor-based Activity Recognition Systems", IETE Tech Rev, Vol. 28, pp. 418-33, 2011.

73. B.P. Mishra, and S. Dehuri, "Parallel Computing Environments: A Review", IETE Tech Rev, Vol. 28, pp. 240-7, 2011.

AUTHORS

Erik Zamora received his B. S. degree from Instituto Politécnico, Mexico, DF in 2002 and his M. S. degree in Computación from CINVESTAV-IPN in 2005. Now, he is doing Ph. D. at the Departamento de Control Automatico at CINVESTAV-IPN. His research interests include SLAM, neural networks, and mobile robot.

E-mail: ezamoa@ctrl.cinvestav.mx

Wen Yu received his B. S. degree from Tsinghua University, Beijing, China in 1990 and his M. S. and Ph. D. degrees, both in Electrical Engineering, from Northeastern University, Shenyang, China in 1992 and 1995, respectively. Since 1996, he has been with CINVESTAV-IPN, Mexico City, Mexico, where he is currently a professor. Dr. Wen Yu serves as an associate editor of *Neurocomputing* and *Journal of Intelligent and Fuzzy Systems*. He is a member of the Mexican Academy of Sciences.

E-mail: yuw@ctrl.cinvestav.mx

DOI: 10.4103/0256-4602.125671; Paper No. TR 288_13; Copyright © 2013 by the IETE