FastSLAM An Improved Particle Filtering Algorithm for Simultaneous Localization and Mapping : A Survey

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This article provides a comprehensive introduction to the field of robotic Simultaneous Localization and Mapping (SLAM), with a focus on FastSLAM. It describes and compares various probabilistic techniques, as they are presently being applied to a vast array of mobile robot SLAM problems. The history of robotic SLAM is also described, along with an extensive list of open research problems.

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1. INTRODUCTION

Simultaneous Localization and Mapping (SLAM) addresses two interrelated problems in mobile robotics concurrently. The first is localization; answering the question "Where am I?" given knowledge of the environment. The second problem is mapping; answering the question "What does the world look like?" Solving these two problems concurrently is difficult because mapping requires the solution to localization but solving localization requires the solution to mapping. To estimate a map, the robot receives sensor measurements, distances to particular landmarks relative to its position. Thus in order to determine a map of the environment, these measurements must be converted into a globally consistent world frame thus requiring the robot location within the world frame. Similarly, estimating the robot's position requires a map simply because it has to be defined in relation to some consistent world frame. This relationship can be addressed by thinking of the problem in terms of uncertainties or probabilities. Within a probabilistic framework the above questions are combined into the single question "Where am I likely to be in the world that I have sensed so far?" [Thrun 2000] Answering this question involves estimating the map while simultaneously estimating the robot location. Absolute knowledge of the world is unrealistic in practice, so uncertainty plays a key role and must be modeled appropriately. The solution within a probabilistic framework provides a method to solve SLAM in the presence of noisy sensors and an uncertain world model [Thrun et al. 2005].

1.1 Why SLAM?

Developing fully automatic robot platforms to operate in dangerous environments would be beneficial for humankind. Replacing humans in dangerous situations is the common application of robotic technology. Such robotic application is the necessity for the robot to collect sensor data about its environment and present this material to humans in an understandable manner. The robot might present the data to the human as a map, or model of the environment along with a path representing the robot's trajectory. Overlaying sensor information on the map allows a human to understand the sensor data more easily [Durrant-Whyte and Bailey 2006]. The difficulty of manually constructing a highly accurate map has motivated the research community to develop autonomous and inexpensive solutions for robotic mapping. Tracking the position and pose of a robot has many applications. The robot needs

to have some representation of its pose within the world for successful navigation. Absolute pose in world coordinates is not always necessary, but an accurate pose relative to the starting location is required for many applications. It becomes possible to navigate unknown terrain by enabling the robot to estimate its pose. Navigation through unknown terrain presents many problems for robotic systems. The robot must be able to not only estimate its own pose but also the pose and potential obstacles in its path. This is not an easy task [Dissanayake et al. 2001].

1.2 A Brief History of SLAM

When mapping and localization were introduced by researchers in the early' 80s, the work focused on solving the two problems of mapping and localization independently. Robotic mapping is the problem of constructing an accurate map of the environment given accurate knowledge of the robot position and motion. The work in robotic mapping typically assumed that the robot location in the environment was known with 100% certainty and focused mainly on incorporating sensor measurements into different map representations of the environment [Durrant-Whyte and Bailey 2006]. Much work has also been done to estimate and maintain the robot position and orientation with an existing complete representation of the environment. In this situation, it is typically assumed that the map is known with 100% certainty and is usually assumed to be static. These algorithms require an a priori map to define the reference frame and the structure of the world. Knowledge of the environment can be in many forms, either a full geometric map representation of the world, or the knowledge of particular landmarks and their locations [Dissanayake et al. 2001].

[Csorba 1997] first introduced the idea of solving both of the above problems, localization and mapping, simultaneously. He developed a probabilistic method of explicitly modeling the spatial-relationships between landmarks in an environment while simultaneously estimating the robot's pose. The map was represented as a set of landmark positions and a covariance matrix was used to model the uncertainty. The framework utilized a Kalman filter to estimate the mean position of each landmark from sensor readings. The introduction of probabilistic methods for robot localization and map creation stimulated a considerable amount of research in this area. The method was called SLAM or Simultaneous Localization and Mapping by [Leonard and Durrant-Whyte 1991] and CML or Concurrent Mapping and Localization by [Thrun et al. 1998]. [Csorba 1997] examined the theoretical framework surrounding solutions to the SLAM problem. This work detailed how correlations arise between errors in the map estimates and the uncertainty which he argues is the fundamental importance in SLAM. He also proved theoretically that it is possible to build a map of an unknown environment accurately through the simultaneous estimation of the robot's pose and the map.

Since the early days of SLAM, a probabilistic approach has become the standard way of modeling the SLAM problem. The different ways in which the probabilistic density functions are represented constitute the differences in each approach. Many issues associated with the Kalman filtering approach have been identified and improved by using Particle-Filtering techniques and a theoretical analysis of the SLAM problem has also been performed. Probabilistic methods are fundamental to solve SLAM because of the inherent uncertainty in the sensor measurements.

1.3 Structure of the Survey

This survey describes techniques that have been used to solve the SLAM problem. It consists of four chapters; chapter one discusses the general introduction of SLAM including why we need SLAM and the brief history of SLAM. Other parts of the survey are organized as follows. In chapter two, a general introduction and exploration of the mathematical preliminaries necessary for solving SLAM in a probabilistic framework are given. Chapter two also includes many different approaches to solve SLAM problem. Chapter three describes the FastSLAM algorithm and improved edition which is FastSLAM 2.0. In chapter four, the conclusion is made and also some open problems for FastSLAM.

2. SLAM

Uncertainty is the fundamental problem to any SLAM algorithm, because sensors never provide perfect data. Sensor measurements are corrupted by noise so they must be appropriately modeled. Different sensors have different accuracy and noise characteristics that must be taken into account. This can be accomplished by using probabilistic models and Bayesian inference methods [Csorba 1997]. In this chapter, the probabilistic techniques in the context of SLAM will be introduced. Bayes rule is discussed and the derivation of Bayesian estimation through recursive filtering leads into the explanation of the Kalman filter which is a popular tool used for solving SLAM problems. Specially, Particle-Filtering techniques for robotics mapping according to Kalman filtering [Welch and Bishop 1995] and their properties will be discussed. Those concepts and techniques are important for SLAM.

2.1 The Description of Problem

Consider a mobile robot moving through an unknown environment. The robot executes controls and collects observations of features in the world. Both the controls and the observations are affected by noise. Simultaneous Localization and Mapping (SLAM) is the process of recovering a map of the environment and the path of the robot from a set of noisy controls and observations [Durrant-Whyte and Bailey 2006]. If the path of the robot were known with certainty, then mapping would be a straightforward problem. When the path of the robot is unknown, error in the robot's path correlates to errors in the map. As a result, the state of the robot and the map must be estimated simultaneously.

2.2 SLAM Posterior

The pose of the robot at time t will be denoted s_t. For robots operating in a planar environment, this pose consists of the robot's x-y position in the plane and its heading direction. The complete trajectory of the robot, consisting of the robot's pose at every time step, will be written as s^t [Thrun et al. 2005].

$$s^t = \{s_1, s_2, \ldots, s_t\}$$

The robot's environment can be modeled as a set of N immobile, point landmarks. Point landmarks are commonly used to represent the locations of features extracted from sensor data. The set of N landmark locations will be written $\{\theta_1, \theta_2, \ldots, \theta_t\}$. For notational simplicity, the entire map will be written as θ [Thrun et al. 2005].

As the robot moves through the environment, it collects relative information about its own motion. Any measurement of the robot's motion will be referred to generically as a control. The control at time t will be written u_t. The set of all controls executed by the robot will be written u^t [Thrun et al. 2005].

$$u^t = \{u_1, u_2, \ldots, u_t\}$$

As the robot moves through its environment, it observes nearby landmarks. In the most common formulation of the SLAM problem, the robot observes both the nearby obstacles and the range to these obstacles. The observation at time t will be written z_t. The set of all observations collected by the robot will be written z^t [Thrun et al. 2005].

$$z^t = \{z_1, z_2, \ldots, z_t\}$$

It is common to assume that in the SLAM literature sensor measurements can be decomposed into information about individual landmarks, such that each landmark observation can be incorporated independently from the other measurements. Thus, we will assume that each observation provides information about the location of exactly one landmark θ_n relative to the robot's current pose s_t. The variable n represents the identity of the landmark being observed. In practice, the identities of landmarks usually can not be observed, as many landmarks may look alike. The identity of the landmark corresponding to the observation z_t will be written as n_t, where $n_t \in \{1, 2, \ldots, N\}$. Landmark identities are commonly referred to as "data associations". The set of all data associations will be written n^t [Thrun et al. 2005].

$$n^t = \{n_1, n_2, \ldots, n_t\}$$

For simplicity, we assume that the robot receives exactly one measurement z_t and executes exactly one control u_t per time. Using the notation defined above, the primary goal of SLAM is to recover the best estimate of the robot pose s_t and the map θ, given the set of noisy observations z_t and controls u_t. In probabilistic terms, the above can be expressed by the following posterior [Thrun et al. 2005]:

$$p(s_t, \theta \mid z_t, u_t, n_t)$$

2.3 Markov Chain

The SLAM problem can be described as a probabilistic Markov chain [Choset et al. 2004]. The current pose of the robot can be written as s_t a probabilistic function of the pose at the previous time step s_{t-1} and the control u_t executed by the robot. This function is referred to as the motion model because it describes how controls drive the motion of the robot. Additionally, the motion model describes how noise in the controls effect uncertainty into the robot's pose estimate. The motion model is written as [Choset et al. 2004]:

$$p(s_t, \mid s_{t-1}, u_t)$$

Sensor observations gathered by the robot are also governed by a probabilistic function, referred to as the measurement model [Choset et al. 2004]. The observation z_t is a function of the observed landmark θ_{nt} and the pose of the robot s_t. The measurement model describes the physics and the error model of the robot's sensor. The measurement model is written as [Choset et al. 2004]:

$$p(z_t, \mid s_t, n_t, \theta)$$

Using the motion model and the measurement model, the SLAM posterior at time t can be computed recursively as a function of the posterior at time t-1 [Choset et al. 2004]. This recursive update rule, known as the Bayes filter for SLAM, is the basis for the SLAM algorithms.

2.4 Recursive Bayesian Filtering

Using Bayesian updating rules at each step of a Markov-chain process is called recursive Bayesian filtering. Recursive Bayesian filtering addresses the problem of estimating a random vector using sensor measurements or other data pertaining to the state [Thrun et al. 1998]. It estimates the posterior probability density function of the state conditioned by the data. In robot localization, we are given some measurements of the world as the robot moves and we wish to estimate the pose of the robot. Recursive Bayesian filtering provides a generalized probabilistic framework [Thrun et al. 2005].

2.5 Kalman Filtering

The most common application of Bayesian filtering is the Kalman filter [Welch and Bishop 1995]. This is a recursive Bayes filter for linear systems. The assumption within the Kalman filter is that the underlying probability density functions for each of the above distributions can be modeled using a Gaussian distribution [Welch and Bishop 1995]. This provides a way of estimating the probability density function. The Kalman filter is used as a state or parameter estimator. It uses the Bayesian framework to update the mean and covariance of a Gaussian probability distribution [Welch and Bishop 1995]. The state to be estimated is a multidimensional vector of random variables that we wish to estimate.

2.6 Extended Kalman Filtering

SLAM algorithms have been developed by restricting the form of the SLAM posterior, the motion model, and the measurement model. Most of the existing SLAM algorithms originate from a paper by [Csorba 1997], which proposed the use of the Extended Kalman Filter (EKF) to estimate the SLAM posterior. The EKF represents the SLAM posterior as a high-dimensional, multivariate Gaussian parameterized by a mean and a covariance matrix [Welch and Bishop 1995]. The mean describes the most likely state of the robot and landmarks, and the covariance matrix encodes the correlations between all pairs of state variables.

The basic Kalman Filter algorithm is the optimal estimator for a linear system with Gaussian noise. The EKF is simply an extension of the basic Kalman Filter algorithm to non-linear systems. The EKF does this by replacing the motion and measurement models with non-linear models around the most-likely state of the

system [Welch and Bishop 1995]. Real-world SLAM problems are rarely linear, yet the EKF still tends to produce very good results in general. The EKF has two substantial disadvantages when applied to the SLAM problem [Csorba 1997]: quadratic complexity and sensitivity to failures in data associations. The second problem with the EKF applies in situations in which the data associations are unknown. The EKF maintains a single data association hypothesis per observation, typically chosen using a maximum likelihood heuristic. If the data association chosen by this heuristic is incorrect, the effect of incorporating this observation into the EKF can never be removed. The following sections will describe some approaches to the SLAM problem.

2.7 Some Approaches to SLAM

2.7.1 *A Solution to SLAM Problem.* In [Dissanayake et al. 2001; Newman 2000], the authors present that the simultaneous localization and map building (SLAM) problem is if it is possible for an mobile robot to start in an unknown location in an unknown environment and then to incrementally build a map of this environment while simultaneously using this map to compute absolute robot location. Starting from the estimation-theoretic foundations of this problem, this paper proves that a solution to the SLAM problem is indeed possible. The underlying structure of the SLAM problem is first elucidated. The authors claim that a proof that the estimated map converges monotonically to a relative map with zero uncertainty is then developed. It is then shown that the absolute accuracy of the map and the robot location reach a lower bound defined only by the initial robot uncertainty. Together, the authors claim that these results show that it is possible for an mobile robot to start in an unknown location in an unknown environment and, using relative observations only, incrementally build a perfect map of the world and to compute simultaneously a bounded estimate of robot location. This paper also describes a substantial implementation of the SLAM algorithm on a robot operating in an outdoor environment using radar to provide relative map observations. The authors claim that this implementation is used to demonstrate how some key issues such as map management and data association can be handled in a practical environment. The results obtained are cross-compared with absolute locations of the map landmarks obtained by surveying.

In conclusion, this paper discusses a number of key issues raised by the solution to the SLAM problem including suboptimal map-building algorithms and map management. The authors claim that this paper makes three principal contributions to the solution of the SLAM problem. First, it proves three key convergence properties of the full SLAM filter. Second, it elucidates the true structure of the SLAM problem and shows how this can be used in developing consistent SLAM algorithms. Finally, it demonstrates and evaluates the implementation of the full SLAM algorithm in an outdoor environment using a radar sensor.

2.7.2 *A Computationally Efficient Solution to the SLAM Problem.* In [Dissanayake et al. 2000], the theoretical basis and a practical implementation of a computationally efficient solution to SLAM are presented. The article shows that it is possible to remove a large percentage of the landmarks from the map without making the map building process statistically inconsistent. Furthermore, the authors claim that it

is shown that the efficiency of the SLAM can be maintained by judicious selection of landmarks, to be preserved in the map, based on their information content. The authors claim that deleting landmarks from the map does not compromise the statistical consistency of the SLAM algorithm. The information content of a landmark is quantified and a strategy to select landmarks to be removed is described. The authors claim that experimental results show that removing suitably selected landmarks does not significantly increase the errors in the estimated vehicle location. However, the computational efficiency of the SLAM process is significantly reduced.

The authors also claim that the key contribution of this paper is a map management strategy that results in a computationally efficient solution to SLAM. Firstly, it shows that any landmark and associated elements of the map covariance matrix can be deleted during the SLAM process without compromising the statistical consistency of the underlying Kalman filter. Secondly, it defines the information content of a landmark and devises a strategy to select landmarks for deletion from the map, while minimizing the loss of information during this process. Finally, it demonstrates and evaluates the implementation of the proposed algorithm in an indoor environment using a scanning laser range finder.

2.7.3 *SLAM with Sparse Extended Information Filters.* In [Dissanayake et al. 2000], the authors propose new algorithms which describe a scalable algorithm for the (SLAM) problem. SLAM is the problem of acquiring a map of a static environment with a mobile robot. The vast majority of SLAM algorithms are based on the extended Kalman filter (EKF). In this paper they advocate an algorithm that relies on the dual of the EKF, the extended information filter (EIF).They show that when represented in the information form, map posteriors are dominated by a small number of links that tie together nearby features in the map. This insight is developed into a sparse variant of the EIF, called the sparse extended information filter (SEIF). SEIFs represent maps by graphical networks of features that are locally interconnected, where links represent relative information between pairs of nearby features, as well as information about the robot's pose relative to the map. They show that all essential update equations in SEIFs can be executed in constant time, irrespective of the size of the map. They also provide empirical results obtained for a benchmark data set collected in an outdoor environment, and using a multi-robot mapping simulation. Their approach is based on the well-known information form of the EKF. Based on the empirical observation that the information matrix is dominated by a small number of entries that are found only between nearby features in the map, they have developed a SEIF. This filter enforces a sparse information matrix, which can be updated in constant time. In the linear SLAM case with known data association, all updates can be performed in constant time; in the nonlinear case, additional state estimates are needed that are not part of the regular information form of the EKF. They have proposed an constant-time coordinate descent algorithm for recovering these state estimates from the information form. They have also proposed an efficient algorithm for data association in SEIFs that requires logarithmic time, assuming that the search for nearby features is implemented by an efficient search tree. The approach has been implemented and compared to the EKF solution. Overall, they find that SEIFs produce results that differ only marginally from that of the EKFs, yet at a much improved

computational speed. Given the computational advantages of SEIFs over EKFs, they believe that SEIFs should be a alternative to EKF solutions when building high-dimensional maps.

2.7.4 *Optimization of the SLAM Algorithm for Real-Time Implementation.* In [Dissanayake et al. 2000], a compressed algorithm was introduced that is very attractive in applications where high frequency external sensor information is available or when the robot navigates for long periods of time in a local area. It is shown that the information gathered in a local area can be incorporated into the robot states and the local map with a computational cost similar to a standard local SLAM algorithm and can then be transferred to an arbitrarily large global map with the implementation of full SLAM algorithm in only one iteration without loss of information. The authors claim that a simplification to the SLAM algorithm has also been proposed with theoretical proofs of the consistency of the approach. Furthermore, it has also been shown with experimental results that, by using a relative map representation, the algorithm becomes very close to optimal. The authors show that with this approach the user can allocate a maximum number of landmarks, according to the computational resources available, and the system will optimally select the ones that provide the maximum information.

2.7.5 *Analysis of Positioning Uncertainty in SLAM.* In [Mourikis and Roumeliotis 2004], the authors study the time evolution of the covariance of the position estimates in single-robot Simultaneous Localization and Mapping (SLAM). The authors claim that a closed-form expression is derived, that establishes a functional relation between the noise parameters of the robot's proprioceptive and exteroceptive sensors, the number of features being mapped, and the attainable accuracy of SLAM. Furthermore, the authors show that it is demonstrated how prior information about the spatial density of landmarks can be utilized in order to compute a tight upper bound on the expected covariance of the positioning errors. The derived closed-form enable the prediction of SLAM positioning performance, without resorting lo extensive simulations, and thus offer an analytical tool for determining the sensor characteristics required to achieve a desired degree of accuracy. The authors claim those simulations experiments are conducted, that corroborate the presented theoretical analysis. The authors also claim that they have presented a method for predicting the positioning performance in SLAM, without the need to resort to extensive simulations or experimentation. This was achieved through a theoretical study of the time evolution of the position estimates covariance, that allowed for the derivation of an analytical upper bound for the positioning uncertainty. The closed-form expression establishes a functional relation between the noise parameters of the robot's sensors, the number of features being mapped, and the accuracy of SLAM. Moreover, when prior information, in the form of a model for the density of landmarks in the area, is available, they can determine a tighter upper hound for the expected value of the steady state covariance of the errors for both the robot and the map features. Thus, a powerful design tool is made available that enables the prediction of the performance of a robot in a mapping application. This can he employed to determine the required accuracy of the robot's sensors, in order to meet task-dependent specifications.

The authors claim that the most restrictive assumption employed in the current work is that the robot can see all landmarks simultaneously. The authors claim that although this is not possible in most real-world applications, the presented analysis can serve as a basis for extensions to more realistic scenarios, where only subsets of the map are visible at each time instant.

2.7.6 *Interactive SLAM using Laser and Advanced Sonar.* In [Mourikis and Roumeliotis 2004], the authors propose a novel approach to mapping for mobile robots that exploits user interaction to semi autonomously create a labeled map of the environment. The robot autonomously follows the user and is provided with a verbal commentary on the current location. At the same time, a metric feature map is generated using fusion of laser and advanced sonar measurements in a Kalman filter based SLAM framework. When mapping is complete, the robot generates an occupancy grid for use in global task planning. The occupancy grid is created using a novel laser scan registration scheme that relies on storing the path of the robot along with associated local SLAM features during mapping, and later recovering the path by matching the associated local features to the final SLAM map. The occupancy grid is segmented into labeled rooms using an algorithm based on watershed segmentation and integration of the verbal commentary. The authors claim that experimental results demonstrate their mobile robot creating SLAM and segmented occupancy grid maps of rooms along a 70 meter corridor, and then using these maps to navigate between rooms.

The authors also claim that they have presented an interactive framework that enables a robot to generate a segmented metric map of an environment by following a tour guide and storing virtual markers created through verbal commands. Throughout the mapping process, the robot performs Kalman filter based SLAM using a fusion of advanced sonar and laser measurements. Two maps are generated at the completion of the mapping process: a SLAM map consisting of point and line features used for localization, and an occupancy grid for task planning. Generation of an accurate occupancy grid is central to their framework, and has been addressed with the development of a novel technique for laser scan registration. During mapping, the location of the robot and an associated laser scan are periodically recorded, along with several local features in the current SLAM map. The path of the robot can be recovered later by matching the stored local features to points in the final SLAM map using a modification of the laser scan matching algorithm. An occupancy grid consistent with the SLAM map is recovered by overlaying the laser scans on the corrected robot path. The authors show that experimental results have demonstrated the necessity of path correction, and verify that their approach generates accurate occupancy grids. This paper has also introduced a novel method for interactive segmentation of the occupancy grid, based on the watershed algorithm with an additional merging stage guided by the verbally generated markers. The authors claim that this approach was successfully demonstrated to segment the map of an office environment into six labeled regions. The segmented map was used to plan a path between rooms, but knowledge of the extent of free space in each room could also be utilized for tasks such as floor cleaning.

2.7.7 *Combinatorial maps for SLAM.* In [Dufourd et al. 2004], the authors claim that in this article they focus on environment models for the well-known Simultaneous Localization and Map building (SLAM) problem, which has received considerable attention in the robotics community over the past few years. First, they compare different existing map representations to discuss their advantages and limitations in the scope of indoor robotics applications. Then they define a highly structured map model which combines different kind of representations, including space-based, grid-based as well as Feature based formats. This model also provides topological information such as adjacency links, which are similar to the topological layer used in geographical information systems. They explain how to build and update map according to this model, using a mobile robot equipped with a laser scanner and underline how the structure of their representation may increase robustness in a Kalman-based SLAM process. Finally, they show same preliminary experiments and propose a few perspectives for this work.

The authors also claim that they have defined a highly structured and consistent map model for SLAM which combines different representation modes: frontier-based, space-based, grid based and topological, they have also explained how to build indoor maps according to this model using an EKF framework maintaining all cross-correlation parameters. The high-level structure of the model induces more complex processing to build the map but in return, it is likely to improve SLAM robustness and provides useful information for global spatial reasoning and planning. Moreover, the similarities with geographical models offer several advantages: GIS classical queries could be transposed to robotics applications and GIS manipulation operations could be used to manage the maps built by robots. In the future, we can even imagine robotic vehicles which would complete existing GIS outdoor maps with their own indoor maps in an autonomous way. The authors also claim that the preliminary experiments are encouraging although they need more extensive tests to validate their system.

2.7.8 *SmartSLAM.* In [Asmar et al. 2004], the authors claim that they propose to extend SLAM to multi-environments. In SmartSLAM, the robot first classifies its entourage using environment recognition code and then performs SLAM using landmarks that are appropriate for its surrounding milieu. The authors explain that one thousand images of various indoor and outdoor environments were collected and used as training data for a three-layered feed forward back propagation neural meshwork. This neural network was then tested on two sets of query images of indoor environments and another two sets of outdoor environments, yielding 83% and 95% correct classification rules for the indoor images and 80% and 79% success rates for the outdoor images.

The authors also claim that the contribution of this paper is in two aspect. Firstly, this is the first algorithm that performs SLAM across multi environments. SmartSLAM uses environment recognition as a primer for feature selection. The second contribution of this paper is in the area of environment recognition and classification. SmartSLAM classifies images using learning alone. A neural network is trained to classify indoor and outdoor environments.

Future work will include a more comprehensive list of environments and investigate a methodology for feature representation and selection.

2.7.9 *Sequential 3D-SLAM.* In [Kohlhepp et al. 2004], the authors claim that reliable mapping and self-localization in three dimensions while moving is essential to survey inaccessible work spaces or to inspect technical plants autonomously. Their solution to this 3D SLAM problem is novel in several respects. First a new rotating laser-scanning setup is presented for acquiring point clouds and reducing them to surface patches in real time. Second, the SLAM algorithms work entirety on highly reduced, attributed surface models and in 3D. Third, The authors claim that they propose a novel system architecture of an Extended Kalmam filter (EKF) for 3D position tracking, cooperating with a 3D range image understanding system for matching, aligning, and integrating overlapping range views. The system is demonstrated by an indoor exploration tour.

The authors also claim that they presented a new SLAM system concept working entirely in 3D and with attributed surface models. A novel rotating laser scanner continuously captures dense, foveal range views which are reduced to surface patches exploiting the parameter space topology. For sequential map building, an EKF provides coarse pose estimation from navigation sensors while range image object recognition and locating system provides precise alignment of overlapping range views. Both subsystems propagate their pose uncertainties individually. The authors show that navigation based uncertainty effectively restricts the search space, and the map based uncertainty in turn resets the EKF estimates. Preliminary results from a small office exploration tour indicate that the crude surface maps produced are accurate and adequate for mobile action planning. One next step will be to extract generalized cylinder surfaces for plant exploration.

The authors finally claim that global pose correction not covered in this article is ongoing research. An elastic graph having as its nodes a limited number of overlapping sub maps with time-varying poses is the key concept to identify and correctly close cycles in the work space, and to propagate global pose corrections over the network.

2.7.10 *Mobile robot SLAM for line-based environment representation.* In [Garulli et al. 2005], the authors present an algorithm for solving the simultaneous localization and map building (SLAM) problem, a key issue for robot navigation in unknown environments. The authors claim that the considered scenario is that of a mobile robot using range scans, provided by a 2D laser rangefinder, to update a map of the environment and simultaneously estimate its position and orientation within the map. The environment representation is based on linear features whose parameters are extracted from range scans, while the corresponding covariance matrices are computed from the statistical properties of the raw data. Simultaneous update of robot pose and linear feature estimates is performed via extended Kalman filtering. The authors claim that experimental tests performed within a real-world indoor environment demonstrate the effectiveness of the proposed SLAM technique. The authors show that by adopting a line-based representation of the environment, the problem is cast as a state estimation problem and solved via extended Kalman filtering. The authors also claim that the results of experimental validation, carried out using the mobile platform Pioneer 3AT, confirm the viability of the proposed approach in quite complex indoor environments.

2.8 Summary

In this chapter we have learned the necessary mathematics that makes it possible to solve SLAM in a probabilistic framework. We first introduced the notion of probabilities which led into the idea of Bayesian estimation. Most algorithms work on the assumption that the current state estimate subsumes the history of its past states so we introduced the Markov chain. The Kalman filter and some of its variants were discussed in detail which help us to understand typical SLAM schemes, since the most common implementations of SLAM use Kalman filtering at. Finally, many different approaches to solving the SLAM problem have been introduced. The most standard approach is the Kalman filter based approach where both the map and pose are encoded in the state vector. The state is defined based on the mean of the Gaussian probability distribution and a covariance matrix to interact between elements in the state vector. In the following chapter, I will introduce the new algorithm to solve SLAM problem which is FastSLAM.

[Montemerlo et al. 2002] FastSLAM factors the SLAM posterior over time using the path of the robot. The resulting algorithm scales logarithmically with the number of landmarks in the map, which is sufficient to process maps with millions of features. FastSLAM samples over potential robot paths, instead of maintaining a parameterized distribution of solutions like the EKF. This enables FastSLAM to apply different data association hypotheses to different solutions represented under the SLAM posterior.

Please see attachment table one for summary of above section.

3. FASTSLAM

Each control or observation collected by the robot only constrains a small number of state variables. Controls probabilistically constrain the pose of the robot relative to its previous pose, while observations constrain the positions of landmarks relative to the robot. It is only after a large number of these probabilistic constraints are incorporated that the map will be fully correlated. The EKF [Welch and Bishop 1995], which makes no assumptions about structure in the state variables, fails to take advantage of this scarcity over time. In this chapter, the survey will concentrates on FastSLAM [Montemerlo et al. 2002], an alternative approach to SLAM that is based on particle filtering. FastSLAM exploits conditional independences that are a consequence of the sparse structure of the SLAM problem to factor the posterior into a product of low dimensional estimation problems. The resulting algorithm scales efficiently to large maps and is robust to significant ambiguity in data association.

3.1 Particle Filtering and Factored Posterior

The Kalman Filter and the EKF represent probability distributions using a parameterized model [Welch and Bishop 1995]. Particle filters [Thrun 2002], on the other hand, represent distributions using a finite set of sample states, or particles. Regions of high probability contain a high density of particles, whereas regions of low probability contain few or no particles. Given enough samples, this non-parametric representation can approximate arbitrarily complex, multi-modal distributions. Given this representation, the Bayes Filter update equation can be

implemented using a simple sampling procedure. The capability to track multimodal beliefs and include non-linear motion and measurement models makes the performance of particle filters particularly robust. However, the number of particles needed to track a given belief may, in the worst case, scale exponentially with the dimensionality of the state space. Standard particle filtering algorithms are restricted to problems of relatively low dimensionality. The robot path posterior is of low dimensionality and can be estimated efficiently using a particle filter. We call such kind of algorithms FastSLAM, based on the Rao-Blackwellized particle filter [Montemerlo et al. 2002]. The majority of SLAM approaches are based on estimating the posterior over maps and robot pose.

$$p(s_t, \theta \mid z^t, u^t, n^t)$$

FastSLAM computes a slightly different quantity, the posterior over maps and robot path.

$$p(s^t, \theta \mid z^t, u^t, n^t)$$

Given knowledge of the robot's path, an observation of one landmark will not provide any information about the position of any other landmark. We could estimate the position of every landmark as an independent quantity. This means that the SLAM posterior can be factored into a product of simpler terms [Montemerlo et al. 2002]. This factorization, first developed by [Murphy 1999], states that the SLAM posterior can be separated into a product of a robot path posterior, and N landmark posteriors conditioned on the robot's path. It follows directly from the structure of the SLAM problem.

3.2 FastSLAM 1.0

In [Montemerlo et al. 2002], the authors propose a new algorithm called FastSLAM, an algorithm that recursively estimates the full posterior distribution over robot pose and landmark locations, yet scales logarithmically with the number of landmarks in the map. The authors explain that this algorithm is based on an exact factorization of the posterior into a product of conditional landmark distributions and a distribution over robot paths. The algorithm has been run successfully on as many as 50,000 landmarks, environments far beyond the reach of previous approaches.

The authors also claim that the FastSLAM algorithm was tested extensively under various conditions. The authors show that real-world experiments were complimented by systematic simulation experiments, to investigate the scaling abilities of the approach. The authors claim that experimental results demonstrate the advantages and limitations of the FastSLAM algorithm on both simulated and real world data.

The FastSLAM algorithm is an efficient new solution to the concurrent mapping and localization problem. This algorithm utilizes a Rao-Blackwellized representation of the posterior, integrating particle filter and Kalman filter representations. The authors show that in FastSLAM, landmark estimates are efficiently represented using tree structures. The authors finally claim that experimental results illustrate that FastSLAM can build maps with orders of magnitude more landmarks than

previous methods. They also demonstrate that under certain conditions, a small number of particles work well regardless of the number of landmarks.

3.2.1 *FastSLAM Algorithm with unknown data association.* In [Montemerlo and Thrun 2003], the authors propose a new algorithms which show that FastSLAM also substantially outperforms the EKF in environments with ambiguous data association. The performance of the two algorithms is compared on a real world data set with various levels of odometric noise. In addition, this article shows that how negative information can be incorporated into FastSLAM in order to improve the accuracy of the estimated map.

The authors use the University of Sydney's Victoria Park data set. An instrumented vehicle with a laser rangefinder was driven through Victoria Park. Encoders on the vehicle recorded velocity and steering angle. Ranges and bearings to nearby trees were extracted from the laser data using a local minima detector. The vehicle was driven around the park for approximately 30 minutes, covering a distance of over 4 km. Filter accuracy was calculated by comparing the estimated vehicle path with GPS. The authors claim that the result of experiment comes as that the performance of FastSLAM and the EKF are comparable.

The authors also claim that an extension of the FastSLAM algorithm to the case of unknown data association. In addition to sampling over robot paths, this formulation of FastSLAM also samples over potential data associations. The authors explain that the resulting algorithm consistently outperformed the Extended Kalman Filter on a real world set with various levels of odometric noise. In addition, it has shown how to incorporate negative information into FastSLAM. The authors show that this technique is not specific to FastSLAM and can also be applied to other SLAM algorithms, including the EKF. The authors claim that use of negative evidence results in a measurable decrease in the number of false landmarks, especially if the feature detector being used generates a large number of spurious features.

3.2.2 *Real Time Data Association for FastSLAM.* In [Nieto et al. 2003], the authors propose a new algorithm which is a real-world implementation of FastSLAM, an algorithm that recursively estimates the full posterior distribution of both robot pose and landmark locations. In particular, they present an extension to FastSLAM that addresses the data association problem using a nearest neighbor technique. Building on this, they also present a novel multiple hypotheses tracking implementation to handle uncertainty in the data association. Finally an extension to the multi-robot case is introduced. Their algorithm has been run successfully using a number of data sets obtained in outdoor environments.

The authors present experimental results that demonstrates the performance of the algorithms when compared with standard Kalman Filter-based approaches. The authors claim that it can be seen that the overall error is smaller in the centralized algorithm. The filter was run with 500 Particles when the robots were working independently and with 800 particles for the multi-robot case.

3.2.3 *FastSLAM for Generating Maps of Cyclic Environments.* In [Haehnel et al. 2003], the authors propose a new algorithm combines particle filtering and scan matching. In their approach scan matching is used for minimizing odometric

errors during mapping. A probabilistic model of the residual errors of scan matching process is then used for the resampling steps. The authors show that in this way the number of samples required is seriously reduced. Simultaneously they reduce the particle depletion problem that typically prevents the robot from closing large loops. They present extensive experiments that illustrate the superior performance of their approach compared to previous approaches.

The authors claim that the approach described above has been implemented and tested using different robotic platforms and in different environments as well as in extensive simulation runs. The authors show that in all experiments, they found out that the system can operate online and can also robustly close large and nested loops.

The authors also claim that a highly efficient algorithm for simultaneous mapping and localization using laser scans that combines a scan matching procedure with particle filtering. The scan matching routine is used to transform sequences of laser measurements into odometry measurements. The corrected odometry and the remaining laser scans are then used for map estimation in the particle filter. The lower variance in the corrected odometry reduces the number of necessary resampling steps and this way decreases the particle depletion problem. The authors explain that in practical experiments they demonstrated that their approach allows to learn maps of large-scale environments in real-time with as few as 100 samples. Simultaneously, it outperforms previous approaches with respect to robustness and efficiency.

3.2.4 *Exploration with Active Loop-Closing for FastSLAM.* In [Stachniss et al. 2004], the authors propose a new algorithm that a novel and integrated approach that combines autonomous exploration with simultaneous localization and mapping. Their method uses a grid-based version of the FastSLAM algorithm and at each point in time considers actions to actively close loops during exploration. The authors claim that by re-entering already visited areas the robot reduces its localization error and this way learns more accurate maps.

The authors also claim that their approach has been implemented and evaluated in a series of real world and simulation experiments. For the real world experiments they used an iRobot B21r robot and an ActivMedia Pioneer II robot. Both are equipped with a laser range finder. For the simulation experiments they used the real-time simulator of the Camegie Mellon Robot Navigation Toolkit. This simulator generates realistic noise in the odometry and laser range sensor data. The authors show that experimental results presented in their paper illustrate the advantage of their method over pervious approaches lacking the ability to actively dose loops.

The authors explain that they presented a novel approach for active loop-closing during autonomous exploration. They combined a particle filter for localization and mapping with a frontier-based exploration technique extended by the ability to actively close loops. Their algorithm forces the robot to traverse previously visited loops again and this way reduces the uncertainty in the pose estimation. The authors claim that as a result, they obtain more accurate maps compared to standard combinations of SLAM algorithms with exploration techniques. One general problem of FastSLAM is that the number of particles needed to build an

accurate map is not known in advance. Even their technique does not provide tools to estimate this quantity but it produces better maps with a given number of particles compared to a naive combination of frontier-based exploration with FastSLAM.

3.2.5 *Consistency of the FastSLAM Algorithm.* In [Stachniss et al. 2004], the authors present an analysis of FastSLAM a Rao-Blackwellized particle filter formulation of simultaneous localization and mapping. It shows that the algorithm degenerates with time, regardless of the number of particles used or the density of landmarks within the environment, and will always produce optimistic estimates of uncertainty in the long-term. The authors claim that FastSLAM behaves like a non-optimal local search algorithm; in the short-term it may produce consistent uncertainty estimates but, in the long-term, it is unable to adequately explore the state-space to be a reasonable Bayesian estimator. However, the number of particles and landmarks does affect the accuracy of the estimated mean and, given sufficient particles, FastSLAM can produce good non-stochastic estimates in practice. The authors explain that FastSLAM also has several practical advantages, particularly with regard to data association, and will probably work well in combination with other versions of stochastic SLAM, such as EKF-based SLAM.

The authors also claim that their results show that the rapid loss of particle diversity prevents a consistent long-term estimate of the joint state. The quality of the FastSLAM results in the literature indicates that it is quite effective in practice. The authors show that they would suggest that the accuracy of these results is testament to quality of the sensors used rather than to the ability of the FastSLAM algorithm. In essence, FastSLAM provides a non-optimal search, over a finite time-horizon, for the most likely trajectory. In practice FastSLAM may produce quite accurate results in terms of deviation from the true state. The authors show that the final quality of this result is dependent on sensor precision. However, FastSLAM's estimate of its accuracy soon becomes optimistic; it tends to underestimate its own uncertainty. In other words, a higher density of landmarks, or equivalently a more precise sensor or more frequent observations, will improve accuracy in terms of real errors, but it will also speed up particle depletion. Therefore, the authors explain that in the long-term, FastSLAM is an inconsistent stochastic filter but, as a heuristic estimator, where only the mean or mode is valued, it can be both tractable and highly accurate. In the short-term, FastSLAM might produce consistent results given a sufficient number of particles. It also has practical properties that make it an attractive short-term estimator, particularly the ability to perform an intuitive type of multi-hypothesis data association.

3.2.6 *Summary of FastSLAM 1.0.* This above section presented FastSLAM, a SLAM algorithm based on particle filtering. FastSLAM [Montemerlo et al. 2002] samples over robot pose and data associations, and computes the positions of the landmarks conditioned on each particle. Per-particle data association factors robot pose uncertainty out of the data association problem. Given known data association, the accuracy of FastSLAM approached the accuracy of the EKF given a sufficient number of particles. If the data associations were unknown [Montemerlo and Thrun 2003], then FastSLAM significantly outperformed the EKF on both real

and simulated data sets. The following section will describe an extension of the FastSLAM that addresses this problem.

Please see attachment table two for summary of above section.

3.3 FastSLAM 2.0

Sampling over robot paths leads to efficient scaling and robust data association, however it also has its sgortcones. FastSLAM, and particle filters in general, have some unusual properties. For example, the performance of the algorithm will eventually degrade if the robot's sensor is too accurate [Montemerlo et al. 2002]. This problem occurs when the proposal distribution is poorly matched with the posterior. In FastSLAM [Montemerlo et al. 2002], this happens when the motion of the robot is noisy relative to the observations. This section will describe a modified version of FastSLAM, called FastSLAM 2.0 [Montemerlo et al. 2003], which attempts to solve this problem. FastSLAM 2.0 incorporates the current observation into the proposal distribution, not just the importance weights, in order to better match the posterior. The resulting algorithm is superior to the original FastSLAM algorithm in nearly all respects [Montemerlo et al. 2003].

In [Montemerlo et al. 2003], the authors proposed new algorithm FastSLAM 2.0 which is a modified version of FastSLAM which overcomes important deficiencies of the original algorithm. Authors prove convergence of this new algorithm for linear SLAM problems and provide real-world experimental results that illustrate an order of magnitude improvement in accuracy over the original FastSLAM algorithm.

The authors use systematic experiments showed that FastSLAM 2.0 provides excellent results with surprisingly few particles. The authors show that most of their experiments were carried out using a benchmark data set collected with an outdoor vehicle in Victoria Park. The vehicle path is 3.5km long, and the map is 320 meters wide. The vehicle is equipped with differential GPS that is used for evaluation only. The authors said that this data set is presently the most popular benchmark in the SLAM research community.

The authors also claim that the new FastSLAM algorithm utilizes a different proposal distribution which incorporates the most recent measurement in the pose prediction process. In doing so, it makes more efficient use of the particles, particularly in situations in which the motion noise is high in relation to the measurement noise.

The authors claim that a main contribution of this paper is a convergence proof for FastSLAM with a single particle. This proof is an improvement over previous formal results, which applied to algorithms much less efficient than the current one. In fact, this result is a first convergence result for a constant time SLAM algorithm. The theoretical finding is complemented by experimental results using a standard benchmark data set. The new algorithm is found to outperform the previous FastSLAM algorithm and the EKF approach to SLAM by a large margin. The authors explain that a single particle suffices to generate an accurate map of a challenging benchmark data set. Despite this surprising result, the use of multiple particles is clearly warranted in situations with ambiguous data association. Authors believe that their results illustrate that SLAM can be solved robustly by algorithms that are significantly more efficient than EKF-based algorithms.

The article described a modified version of the FastSLAM algorithm that ad-

dresses the issue of sample impoverishment. FastSLAM 2.0 [Montemerlo et al. 2003] incorporates observations into the proposal distribution of the particle filter in order to better match the posterior distribution. As a consequence, fewer trajectories are thrown out during resampling, and FastSLAM 2.0 is able to maintain correlation information further back in time. The authors claim that results in better performance when the robot's sensor is very accurate, faster convergence, and allows the algorithm to close larger loops.

3.4 Summary

This chapter introduced Particle-Filtering based approaches and discussed their use in solving SLAM and it seems that the research community is leaning towards these types of solutions rather than the Kalman filter based approach [Choset et al. 2004]. This is due to the fact that Particle-filter-based solutions address the core issues in the Kalman filter, namely that a Gaussian model does not necessarily fit the SLAM problem well [Durrant-Whyte and Bailey 2006]. Particle-filtering can represent any probability distribution given enough samples. A popular algorithm in use is FastSLAM which estimates the posterior distribution over robot paths and landmarks [Montemerlo et al. 2002]. The FastSLAM algorithm utilizes a separate Extended Kalman Filter per landmark and a particle filter that samples the robot trajectory. It was possible to accurately solve SLAM using Particle-filters and that it was possible to separate the two problems of mapping and localization.

Researchers claim that FastSLAM works well in practice, however there are some disadvantages to this approach [Montemerlo et al. 2003]. Since the data association problem must be solved on a per-particle basis, each particle contains a different representation of the environment. Merging these multiple maps is nontrivial and computationally expensive. Also, if landmarks are sparse or measurements have high amounts of noise then the FastSLAM algorithm is prone to diverge. This occurs because of the dimensionality of the problem. Since the probability distribution that is estimated is the posterior over robot paths, as time progresses the dimensionality increases linearly. Effectively, this is the core issue of FastSLAM [Stachniss et al. 2004]. In order to maintain a high degree of accuracy, many more particles are required to sample the robot path space which increases the computational requirements of the algorithm. FastSLAM is a hybrid particle-filtering and Kalman filtering algorithm and contains elements of both including their strengths and weaknesses.

4. CONCLUSIONS AND FUTURE WORKS

The goal of this report was to survey major algorithms in the field of robotic Simultaneous Localization and Mapping. This article has described the SLAM problem,the FastSLAM problem, and also the essential methods for solving those SLAM problems and has summarized key implementations and demonstrations of the method. While there are still many practical issues to overcome and some future work to be done.

In [Newman 2000], the author claims that many problems still need to be solved before a mobile robot can provably operate in an entirely unknown environment and research continues on many fronts. Two approaches are of particular interest. First is an information theoretic formulation of the SLAM problem. Such

a formulation may allow active sensing strategies to be developed that maximize the information content of the map or vehicle estimates. Secondly, the efficient and consistent use of sub maps may allow a 'divide and conquer' approach to be adopted in which landmark estimates are only manipulated in local regions of interest and hence allow computation to be significantly reduced. Many potential applications of SLAM require operation in natural, non-man made environments. The successful deployment of a robot in such an environment would constitute a general solution to the mobile robot navigation problem; however this remains an elusive goal. It requires the integration and co-ordination of four key competencies - natural landmark identification, data association, map management and the SLAM algorithm itself. Much successful research has been undertaken within each of these individual areas in isolation. The problem that must now be solved is how to fuse the algorithms and knowledge resulting from this endeavor into a system capable of robustly solving the navigation problem in real time. Until this fusion is accomplished, Simultaneous Localization and Map Building remains a challenging and fascinating problem.

In [Dissanayake et al. 2001], the authors claim that the implementation described in [Dissanayake et al. 2001] is relatively small scale. It does, however, serve to illustrate a range of practical issues in landmark extraction, landmark initialization, data association, maintenance and validation of the SLAM algorithm. The authors claim that the implementation and deployment of a large-scale SLAM system, capable of vehicle localization and map building over large areas, will require further development of these practical issues as well as a solution to the map management problem. However, such a substantial deployment would represent a major step forward in the development of autonomous vehicle systems.

In [Dissanayake et al. 2000], the authors claim that further challenges in this area requires a more rigorous analysis of the information content of landmarks, giving due consideration to the geometrical effects as well as the uncertainty of the landmark location estimate.

In [Guivant and Nebot 2001], the authors claim that future work should address the extension of the compression filter results in decentralized SLAM where different platforms can update their own map with a particular sensor and then transfer all the information gained to the rest of the system. The incorporation of high frequency information increases the exploration range of the SLAM algorithm. This is also another important area of research. If no absolute position data is made available, the system will not be able to navigate for extended periods of time in new areas without returning to known areas. The authors also claim that although standard sensors allow SLAM to perform in significantly large areas, in order to extend this range there are two important problems to be solved: The association of a known revisited area and the back-propagation of the corrections once a large loop is traversed. The first problem looks solvable working with the geometry of the environment, or using more complex data association methods. The other problem is not solved yet and is the subject of current research.

In [Garulli et al. 2005], the authors claim that future directions of research include the integration of additional features in the map and the comparison with different segmentation algorithms as well as with more sophisticated data associa-

tion policies. In this respect, the preliminary promising results have been obtained by simulation experiments. Moreover, the consistency of the line-based map in the long run is under investigation.

In [Diosi et al. 2005], the authors claim that in future work, they intend to extend the system by implementing large loop-closing, and a global localization strategy to determine the pose of the robot anywhere in the SLAM map. Furthermore, visual sensing could lead to a number of improvements by providing additional features for both SLAM and person following. Their recent work in multiple hypothesis laser-based people tracking could also lead to improved people following behavior.

5. ANNOTATIONS

Please see the attachment for more detail.

6. ACKNOWLEDGMENTS

I am gratefully acknowledging the support I received and the benefit I had from extensive discussions on these topics with Dr. R. Frost. I would also like to thank my supervisor, Dr. Wu, for giving me the background knowledge of FastSLAM. Finally, I would like to thank my family, and my girlfriend Yihan for their love, support, and encouragement.

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Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2003. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. *International Joint Conference on Artificial Intelligence 18*, 1151–1156.

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FastSLAM An Improved Algorithm and Solution for Simultaneous Localization and Mapping: A Survey (Annotation)

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Simultaneous localization and mapping with unknown data association using FastSLAM

Montemerlo, M. and Thrun, S. 2003. Simultaneous localization and mapping with unknown data association using fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 2, 1985–1991.

First, this article addressed a problem that The Extended Kalman Filter (EKF) has been the de facto approach to Simultaneous Localization and Mapping (SLAM) problem for nearly fifteen years. However, the EKF has two serious deficiencies that prevent it from being applied to large, real world environments: quadratic complexity and sensitivity to failures in data association.

Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Second, this article proposed new algorithms which show that FastSLAM also substantially outperforms the EKF in environments with ambiguous data association. The performance of the two algorithms is compared on a real world data set with various levels of odometric noise. In addition, this article shows that how negative information can be incorporated into FastSLAM in order to improve the accuracy of the estimated map.

Third, authors use the University of Sydney's Victoria Park data set. An instrumented vehicle with a laser rangefinder was driven through Victoria Park. Encoders on the vehicle recorded velocity and steering angle. Ranges and bearings to nearby trees were extracted from the laser data using a local minima detector. The vehicle was driven around the park for approximately 30 minutes, covering a distance of over 4 km. Filter accuracy was calculated by comparing the estimated vehicle path with GPS. The authors claim that the result of experiment comes as that the performance of FastSLAM and the EKF are comparable.

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Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2003. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. *International Joint Conference on Artificial Intelligence* 18, 1151–1156.

First, reference in the article to previous work by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Second, this article proposed new algorithm FastSLAM 2.0 which is a modified version of FastSLAM which overcomes important deficiencies of the original algorithm. Authors prove convergence of this new algorithm for linear SLAM problems and provide real-world experimental results that illustrate an order of magnitude improvement in accuracy over the original FastSLAM algorithm.

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Finally, this article claims that the new FastSLAM algorithm utilizes a different proposal distribution which incorporates the most recent measurement in the pose prediction process. In doing so, it makes more efficient use of the particles, particularly in situations in which the motion noise is high in relation to the measurement noise. The authors claim that a main contribution of this paper is a convergence proof for FastSLAM with a single particle. This proof is an improvement over previous formal results, which applied to algorithms much less efficient than the current one. In fact, this result is a first convergence result for a constant time SLAM algorithm. The theoretical finding is complemented by experimental results using a standard benchmark data set. The new algorithm is found to outperform the previous FastSLAM algorithm and the EKF approach to SLAM by a large margin. The authors claim that a single particle suffices to generate an accurate map of a challenging benchmark data set. Despite this surprising result, the use of multiple particles is clearly warranted in situations with ambiguous data association. Authors believe that their results illustrate that SLAM can be solved robustly by algorithms that are significantly more efficient than EKF-based algorithms.

This article was cited by Thrun, S., Liu, Y., Koller, D., Ng, A. Y., Ghahramani, Z., and Durrant-Whyte, H. 2003. Simultaneous localization and mapping with sparse extended information filters. *International Journal of Robotics Research* 23, 693–716.

An Efficient FastSLAM Algorithm for Generating Maps of Large-Scale Cyclic Environments from Raw Laser Range Measurements

Hahnel, D., Burgard, W., Fox, D., and Thrun, S. 2003. An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on* 1, 206–211.

First, this article addressed a problem that the ability to learn a consistent model of its environment is a prerequisite for autonomous mobile robots. A particularly challenging problem in acquiring environment maps is that of closing loops; loops in the environment create challenging data association problems.

Gutmann, J.S. and Konolige. K. Incremental mapping of large cyclic environments. *In Proc. of the IEEE Int. Symp. On Computational Intelligence in Robotics and Automation (CIRA)*, 1999.

Second, this article proposed new algorithm combines Rao-Blackwellized particle filtering and scan matching. In their approach scan matching is used for minimizing odometric errors during mapping. A probabilistic model of the residual errors of scan matching process is then used for the resampling steps. This way the number of samples required is seriously reduced. Simultaneously they reduce the particle depletion problem that typically prevents the robot from closing large loops. They present extensive experiments that illustrate the superior performance of their approach compared to previous approaches.

Third, the authors claim that the approach described above has been implemented and tested using different robotic platforms and in different environments as well as in extensive simulation runs. The authors claim that in all experiments, they found out that the system can operate online and can also robustly close large and nested loops.

Finally, this article claims that a highly efficient algorithm for simultaneous mapping and localization using laser scans that combines a scan matching procedure with Rao-Blackwellized particle filtering. The scan matching routine is used to transform sequences of laser measurements into odometry measurements. The corrected odometry and the remaining laser scans are then used for map estimation in the particle filter. The lower variance in the corrected odometry reduces the number of necessary resampling steps and this way decreases the particle depletion problem. The authors claim that in practical experiments they demonstrated that their approach allows to learn maps of large-scale environments in real-time with as few as 100 samples. Simultaneously, it outperforms previous approaches with respect to robustness and efficiency.

This article was cited by Bailey, T., Nieto, J., and Nebot, E., 2006. Consistency of the FastSLAM Algorithm. *Proceedings of 2006 IEEE International Conference on Robotics and Automation*, 424–429

Real Time Data Association for FastSLAM

Nieto, J., Guivant, J., Nebot, E., and Thrun, S. 2003. Real time data association for fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 1, 412–418.

First, this article addressed a problem that FastSLAM uses a modified particle filter to estimate the robot pose. Each particle has an independent EKF running for each landmark in the map to estimate its position. However, the original paper presents results assuming the data association is known, and no sound solution has been provided when data association is unknown.

Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Second, this article proposed new algorithm a real-world implementation of FastSLAM, an algorithm that recursively estimates the full posterior distribution of both robot pose and landmark locations. In particular, they present an extension to FastSLAM that addresses the data association problem using a nearest neighbor technique. Building on this, they also present a novel multiple hypothesis tracking implementation (MHT) to handle uncertainty in the data association. Finally an extension to the multi-robot case is introduced. Their algorithm has been run successfully using a number of data sets obtained in outdoor environments.

Third, the authors claim that experimental results are presented that demonstrate the performance of the algorithms when compared with standard Kalman Filter-based approaches. The authors claim that it can be seen that the overall error is smaller in the centralized algorithm. The filter was run with 500 Particles when the robots were working independently and with 800 particles for the multi-robot case.

Fourth, this article claims that extensions to the FastSLAM algorithm to implement data association. The authors claim that the experimental results performed in a variety of outdoor environments demonstrated the robustness of the algorithms and the ability to handle multiple hypotheses in a very efficient and elegant manner.

Finally, the authors claims future research that use of the algorithm in the bearing-only problem using non-Gaussian representations for the map, implementation of a hybrid SLAM architecture, EKF SLAM-FastSLAM and extension of the current algorithm to implement a decentralized multi-robot SLAM.

This article was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

FastSLAM: A Factored Solution to the Simultaneous Localization and Mapping Problem

Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

First, this article addressed a problem that the ability to simultaneously localize a robot and accurately map its surroundings is considered by many to be a key prerequisite of truly autonomous robots. However, few approaches to this problem scale up to handle the very large number of landmarks present in real environments. Kalman filter-based algorithms, for example, require time quadratic in the number of landmarks to incorporate each sensor observation. A key limitation of EKF-based approaches is their computational complexity.

R. Smith, M. Self, and P. Cheeseman. Estimating uncertain spatial relationships in robotics. In Autonomous Robot Vehicles, Springer, 1990.

Second, this article proposed new algorithm that FastSLAM, an algorithm that recursively estimates the full posterior distribution over robot pose and landmark locations, yet scales logarithmically with the number of landmarks in the map. The authors claim that this algorithm is based on an exact factorization of the posterior into a product of conditional landmark distributions and a distribution over robot paths. The authors claim that the algorithm has been run successfully on as many as 50,000 landmarks, environments far beyond the reach of previous approaches.

Third, the authors claim that the FastSLAM algorithm was tested extensively under various conditions. The authors claim that real-world experiments were complimented by systematic simulation experiments, to investigate the scaling abilities of the approach. The authors claim that experimental results demonstrate the advantages and limitations of the FastSLAM algorithm on both simulated and real world data.

Finally, the authors claims that the FastSLAM algorithm, an efficient new solution to the concurrent mapping and localization problem. This algorithm utilizes a Rao-Blackwellized representation of the posterior, integrating particle filter and Kalman filter representations. The authors claim that in FastSLAM, landmark estimates are efficiently represented using tree structures. The authors claim that experimental results illustrate that FastSLAM can build maps with orders of magnitude more landmarks than previous methods. They also demonstrate that under certain conditions, a small number of particles work well regardless of the number of landmarks.

This article was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2003. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. *International Joint Conference on Artificial Intelligence* 18, 1151–1156.

Exploration with Active Loop-Closing for FastSLAM

Cyrill, S., Dirk, H., and Wolfram, B., 2004. Exploration with Active Loop-Closing for FastSLAM. *Proceedings of 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 1505–1510

First, this article addressed a problem that acquiring models of the environment belongs to the fundamental tasks of mobile robots. In the last few years several researchers have focused on the problem of simultaneous localization and mapping (SLAM). Classic SLAM approaches are passive in the sense that they only process the perceived sensor data and do not influence the motion of the mobile robot.

Dissanayake, G., Durrant-Whyte, H., and Bailey, T. 2000. A computationally efficient solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on* 2, 1009–1014.

Second, this article proposed new algorithm that a novel and integrated approach that combines autonomous exploration with simultaneous localization and mapping. Their method uses a grid-based version of the FastSLAM algorithm and at each point in time considers actions to actively close loops during exploration. The authors claim that by re-entering already visited areas the robot reduces its localization error and this way learns more accurate maps.

Third, the authors claim that their approach has been implemented and evaluated in a series of real world and simulation experiments. For the real world experiments they used an iRobot B21r robot and an ActivMedia Pioneer II robot. Both are equipped with a SICK laser range finder. For the simulation experiments they used the real-time simulator of the Camegie Mellon Robot Navigation Toolkit. This simulator generates realistic noise in the odometry and laser range sensor data. The authors claim that experimental results presented in this paper illustrate the advantage of their method over pervious approaches lacking the ability to actively dose loops.

Fourth, the authors claim that they presented a novel approach for active loop-closing during autonomous exploration. They combined a Rao-Blackwellized particle filter for localization and mapping with a frontier-based exploration technique extended by the ability to actively close loops. Their algorithm forces the robot to traverse previously visited loops again and this way reduces the uncertainty in the pose estimation. The authors claim that as a result, they obtain more accurate maps compared to standard combinations of SLAM algorithms with exploration techniques. One general problem of FastSLAM is that the number of particles needed to build an accurate map is not known in advance. Even their technique does not provide tools to estimate this quantity but it produces better maps with a given number of particles compared to a naive combination of frontier-based exploration with FastSLAM.

Finally, the authors claim that the mayor restrictions of their algorithm are similar to those of FastSLAM, e.g., there are no means to recover from divergence without a complete re-run of the whole algorithm. Such issues are subject of future research.

This article was cited by Stachniss, C., Grisetti, G. and Burgard, W., Recovering particle diversity in a rao-blackwellized particle filter for slam after actively closing

loops. *In Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA)*, 2005.

Consistency of the FastSLAM Algorithm

Bailey, T., Nieto, J., and Nebot, E., 2006. Consistency of the FastSLAM Algorithm. *Proceedings of 2006 IEEE International Conference on Robotics and Automation*, 424–429.

First, this article addressed a problem that FastSLAM in its current form cannot produce consistent estimates in the long-term. Each particle implicitly records a pose history in the statistics of its associated map. Every time a particle is lost due to resampling, an entire map hypothesis is lost and there is depletion in historical information. As a consequence the overall map statistics degrade.

Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Second, this article presents an analysis of FastSLAM a Rao-Blackwellized particle filter formulation of simultaneous localization and mapping. It shows that the algorithm degenerates with time, regardless of the number of particles used or the density of landmarks within the environment, and will always produce optimistic estimates of uncertainty in the long-term. The authors claim that in essence, FastSLAM behaves like a non-optimal local search algorithm; in the short-term it may produce consistent uncertainty estimates but, in the long-term, it is unable to adequately explore the state-space to be a reasonable Bayesian estimator. However, the number of particles and landmarks does affect the accuracy of the estimated mean and, given sufficient particles, FastSLAM can produce good non-stochastic estimates in practice. The authors claim that FastSLAM also has several practical advantages, particularly with regard to data association, and will probably work well in combination with other versions of stochastic SLAM, such as EKF-based SLAM.

Third, the authors claim that their results show that the rapid loss of particle diversity prevents a consistent long-term estimate of the joint state PDF. And yet, the quality of the FastSLAM results in the literature indicates that it is quite effective in practice. The authors claim that they would suggest that the accuracy of these results is testament to quality of the sensors used (typically a scanning range laser) rather than to the ability of the FastSLAM algorithm. In essence, FastSLAM provides a non-optimal search, over a finite time-horizon, for the most likely trajectory. In practice FastSLAM may produce quite accurate results in terms of deviation from the true state. The authors claim that the final quality of this result is dependent on sensor precision. However, FastSLAM's estimate of its accuracy soon becomes optimistic; it tends to underestimate its own uncertainty. In other words, a higher density of landmarks, or equivalently a more precise sensor or more frequent observations, will improve accuracy in terms of real errors, but it will also speed up particle depletion. Therefore, the authors claim that in the long-term, FastSLAM is an inconsistent stochastic filter but, as a heuristic (non-stochastic) estimator, where only the mean or

mode is valued, it can be both tractable and highly accurate. In the short-term, FastSLAM might produce consistent results given a sufficient number of particles. It also has practical properties that make it an attractive short-term estimator, particularly the ability to perform an intuitive type of multi-hypothesis data association. The authors claim that one possible use for FastSLAM is as a front-end SLAM component that processes current data and forms a short-term local map, and later converts this map to a joint Gaussian PDF and merges it with a global EKFSLAM map.

This article was cited by Kristopher, R., Beevers and Huang, W. H., 2006. Consistency of the FastSLAM Algorithm. *Proceedings of 2006 IEEE International Conference on Robotics and Automation*, 424–429

A Computationally Efficient Solution to the Simultaneous Localization and Map Building (SLAM) Problem

Dissanayake, G., Durrant-Whyte, H., and Bailey, T. 2000. A computationally efficient solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on* 2, 1009–1014.

First, this article addressed a problem that The theoretical basis of the solution to the simultaneous localization and map building (SLAM) problem where an autonomous vehicle starts in an unknown location in an unknown environment and then incrementally build a map of landmarks present in this environment while simultaneously using this map to compute absolute vehicle location is now well understood. The authors claim that although a number of SLAM implementations have appeared in the recent literature, the need to maintain the knowledge of the relative relationships between all the landmark location estimates contained in the map makes SLAM computationally intractable in implementations containing more than few tens of landmarks.

Dissanayake, M.W.M.G., Newman, P., Durrant-Whyte, H.F., Clark, S. and Csobra, S. An experimental and theoretical investigation into simultaneous localization and map building (slam). In Proc. 6th International Symposium on Experimental Robotics, pages 171 - 180, Sydney, Australia, March 1999.

Second, the authors claim that in this article the theoretical basis and a practical implementation of a computationally efficient solution to SLAM is presented. The article shows that it is indeed possible to remove a large percentage of the landmarks from the map without making the map building process statistically inconsistent. Furthermore, the authors claim that it is shown that the efficiency of the SLAM can be maintained by judicious selection of landmarks, to be preserved in the map, based on their information content.

Third, the authors use a practical implementation of the proposed simultaneous localization and map building (SLAM) algorithm on an indoor robot. The robot is equipped with a Laser range finder which provides a two-dimensional range scans. A feature detector is used to extract location of landmarks with respect to the vehicle.

The authors claim that this implementation serves to highlight the effectiveness of the proposed map management strategy.

Fourth, the authors claim that deleting landmarks from the map does not compromise the statistical consistency of the SLAM algorithm. The information content of a landmark is quantified and a strategy to select landmarks to be removed is described. The authors claim that experimental results show that removing suitably selected landmarks does not significantly increase the errors in the estimated vehicle location. However, the computational efficiency of the SLAM process is significantly reduced. The authors claim that further challenges in this area remains a more rigorous analysis of the information content of landmarks, giving due consideration to the geometrical effects as well as the uncertainty of the landmark location estimate.

Finally, Authors claim that the key contribution of this paper is a map management strategy that results in a computationally efficient solution to SLAM. Firstly, it shows that any landmark and associated elements of the map covariance matrix can be deleted during the SLAM process without compromising the statistical consistency of the underlying Kalman filter. Secondly, it defines the information content of a landmark and devises a strategy to select landmarks for deletion from the map, while minimizing the loss of information during this process. Finally, it demonstrates and evaluates the implementation of the proposed algorithm in an indoor environment using a scanning laser range finder.

This article was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

The SPmap: A Probabilistic Framework for Simultaneous Localization and Map Building

Castellanos, J. A., Montiel, J. M. M., Neira, J., and Tardos, J. D. 1999. The SPmap: A probabilistic framework for simultaneous localization and map building. *IEEE Transactions on Robotics and Automation* 15, 948–952.

First, this article addressed a problem that successful path planning and navigation of a mobile robot in a human-made indoor environment requires the availability of both a sufficiently reliable estimation of the current vehicle location, and a sufficiently precise map of the navigation area. A priori model maps are rarely available, costly to obtain, and when they are available, they usually introduce inaccuracies in the planning tasks. An automatic construction of the map of the environment in which the robot navigates would be desirable, and it has become an important research direction in today's robotics community.

Castellanos, J. A. 1998. Mobile robot localization and map building: A multi-sensor fusion approach. Dept. Inform. Eng. Syst., Univ. Zaragoza, Maria de Luna, Spain.

Second, this article describes a rigorous and complete framework for the simultaneous localization and map building problem for mobile robots: the symmetries and perturbations map (SPmap), which is based on a general probabilistic representation of uncertain geometric information. They present a complete

experiment with a LabMateTM mobile robot navigating in a human-made indoor environment and equipped with a rotating two-dimensional (2-D) laser rangefinder. Experiments validate the appropriateness of their approach and provide a real measurement of the precision of the algorithms.

Finally, the authors claim that they have presented a complete experiment, where a LabMate mobile robot equipped with a rotating 2-D laser rangefinder navigated indoors. The authors claim that experimentation showed the importance of maintaining correlations between entities. Satisfactory results have been obtained concerning the problem of revisiting previously learned places of the navigation area. Their recent work has motivated them with further extensions of the concept of SPmap, both to extent its applicability to real-life environments and to increase its robustness: 1) sensor cooperation to obtain more robust and reliable observations from the navigation area; 2) increase in the structuration and the semantical contents of the representation toward a topological description where human-language-like instructions could be commanded to the vehicle; 3) search for optimal representations of the navigation area to reduce the complexity of the current approach, when larger environments are considered; 4) design of strategies to maintain the constructed map, such as those required to remove features not visible for a long time.

This article was cited by Hahnel, D., Burgard, W., Fox, D., and Thrun, S. 2003. An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on* 1, 206–211.

A Real-Time Algorithm for Mobile Robot Mapping With Applications to Multi-Robot and 3D Mapping

Thrun, S., Burgard, W., and Fox. D. 2000. A real-time algorithm for mobile robot mapping with applications to multi-robot and 3D mapping. *In Proc. of the IEEE International Conference on Robotics & Automation (ICRA)*, 722-729.

First, this article addressed a problem that Building maps of indoor environments is a pivotal problem in mobile robotics. The problem of mapping is often referred to as the concurrent mapping and localization problem, to indicate its chicken-and-egg nature: Building maps when a robot's locations are known is relatively straightforward, as early work by Moravec and Elfes has demonstrated more than a decade ago. Conversely, localizing a robot when a map is readily available is also relatively well-understood, as a flurry of algorithms has successfully demonstrated. In combination, however, the problem is hard. Recent progress has led to a range of new methods. Most of these approaches build maps incrementally, by iterating localization and incremental mapping for each new sensor scan the robot receives. While these methods are fast and can well be applied in real-time, they typically fail when mapping large cyclic environments. This is because in environments with cycles, the robot's cumulative error can grow without bounds, and when closing the cycle error has to be corrected backwards in time (which most existing methods are incapable of

doing). Recent families of probabilistic methods based on EM overcome this problem. EM searches the most likely map by simultaneously considering the locations of all past scans, using a probabilistic argument for iterative refinement during map construction. While these approaches have successfully mapped large cyclic environments, they are batch algorithms that cannot be run in real-time. Thus, a natural goal is to devise methods that combine the advantages of both methodologies, without giving up too much of the full power of EM so that large cycles can be mapped in real time. Most previous approaches also construct 2Dmaps only, and they only address single-robot mapping.

Thrun, S., Fox, D., and Burgard, W. 1998. A probabilistic approach to concurrent mapping and localization for mobile robots. *Machine Learning*, 31.

Second, this article present an incremental method for concurrent mapping and localization for mobile robots equipped with 2D laser range finders. The authors claim that the approach uses a fast implementation of scan-matching for mapping, paired with a sample-based probabilistic method for localization. Compact 3D maps are generated using a multi-resolution approach adopted from the computer graphics literature, fed by data from a dual laser system. Their approach builds 3D maps of large, cyclic environments in real-time. It is remarkably robust. The authors claim that experimental results illustrate that accurate maps of large, cyclic environments can be generated even in the absence of any odometric data.

Finally, this authors claim that their approach combines ideas from incremental mapping (maximum likelihood, incremental map construction) with ideas of more powerful, non-incremental approaches (posterior estimation, backwards correction). The authors claim that the result is a fast and robust algorithm for real-time mapping of indoor environments, which extends to multi-robot mapping and mapping in 3D. A fast algorithm was employed to generate compact 3D models of indoor environments. The authors claim that experimental results illustrated that large-scale environments can be mapped in real-time. The resulting maps were highly accurate. They also demonstrated that their approach can generate 3D maps, and it can fuse information collected though multiple robot platforms. The authors claim that when compared to EM, the ability to generate maps in real time comes at a price of increased brittleness. EM is a principled approach to finding the best map, which simultaneously revises beliefs arbitrarily far in the past—which makes it necessarily inapplicable in real-time. However, their approach inherits some of the power of EM by using posterior estimations and a fast mechanism for backwards revision, specifically tuned for mapping cyclic environments. The authors claim that as a result, their approach can handle a large range of environments in real-time. Nevertheless, their approach surpasses previous incremental approaches in robustness, specifically in environments with cycles. Their results make them confident that the approach is very robust to errors, in particular odometry errors.

This article was cited by Hahnel, D., Burgard, W., Fox, D., and Thrun, S. 2003. An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on* 1, 206–211.

Optimization of the Simultaneous Localization and Map-Building Algorithm for Real-Time Implementation

Guivant, J. and Nebot, E. June 2001. Optimization of the simultaneous localization and map building algorithm for real time implementation. *IEEE Transaction of Robotic and Automation*, 318-325.

First, reference in the article to previous work by Thrun, S. Fox, D. and Bugard, W. May 1998. Probabilistic mapping of an environment by a mobile robot. *In Proc. IEEE Int. Conf. Robot. Automat., Belgium*, 1546–1551.

Second, this article addresses real-time implementation of the simultaneous localization and map-building (SLAM) algorithm. It presents optimal algorithms that consider the special form of the matrices and a new compressed filter that can significantly reduce the computation requirements when working in local areas or with high frequency external sensors. It is shown that by extending the standard Kalman filter models the information gained in a local area can be maintained with a low cost, and then transferred to the overall map in only one iteration at full SLAM computational cost. The authors claim that additional simplifications are also presented that are very close to optimal when an appropriate map representation is used. Finally the algorithms are validated with experimental results obtained with a standard vehicle running in a completely unstructured outdoor environment.

Third, the authors claim that a compressed algorithm was introduced that is very attractive in applications where high frequency external sensor information is available or when the vehicle navigates for long periods of time in a local area. It is shown that the information gathered in a local area can be incorporated into the vehicle states and the local map with a computational cost similar to a standard local SLAM algorithm and can then be transferred to an arbitrarily large global map with the implementation of full SLAM algorithm in only one iteration without loss of information. The authors claim that a simplification to the SLAM algorithm has also been proposed with theoretical proofs of the consistency of the approach. Furthermore, it has also been shown with experimental results that, by using a relative map representation, the algorithm becomes very close to optimal. The authors claim that with this approach the user can allocate a maximum number of landmarks, according to the computational resources available, and the system will optimally select the ones that provide the maximum information. The authors claim that future work will address the extension of the compression filter results in decentralized SLAM where different platforms can update their own map with a particular sensor and then transfer all the information gained to the rest of the system. The incorporation of high frequency information increases the exploration range of the SLAM algorithm. This is also another important area of research. If no absolute position data is made available, the system will not be able to navigate for extended periods of time in new areas without returning to known areas.

Finally, The authors claim that although standard sensors allow SLAM to perform in significantly large areas, in order to extend this range there are two important

problems to be solved: The reregistration (association) of a known revisited area and the back-propagation of the corrections once a large loop is traversed. The first problem looks solvable working with the geometry of the environment, or using more complex data association methods. The other problem is not solved yet and subject of current research.

This article was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

On the Structure and Solution of the Simultaneous Localization and Map Building Problem

Newman, P. 2000. On the structure and solution of the simultaneous localization and map building problem. Ph.D. thesis, University of Sydney.

First, reference in the article to previous work by Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 1999. A solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, IEEE Transactions on* 17, 229–241.

Second, this thesis is concerned with the simultaneous localization and map building (SLAM) problem. The SLAM problem asks if it is possible for an autonomous vehicle to start in an unknown location in an unknown environment and then to incrementally build a map of this environment while simultaneously using this map to compute absolute vehicle location. The map and robot location estimates obtained from a successful SLAM system provide essential information upon which high level tasks such as path planning are predicated. A practicable solution to the SLAM problem is of inestimable value in the quest to create a truly autonomous mobile robot. The authors claim that the thesis has three principal theoretical contributions. The first is the elucidation of the structure of the SLAM problem. This is achieved by the analysis of a conventional and well known SLAM algorithm using global coordinates called, in this thesis, the Absolute Map Filter or AMF. Using this algorithm, three convergence theorems central to the SLAM problem are proved for the first time. They prove that the uncertainty in the estimated map decreases monotonically and achieves a defined lower bound. Furthermore, in the limit as the number of landmark observations increases, the relationship between landmarks becomes perfectly known. These proofs constitute the second theoretical contribution of the thesis. The third principal theoretical contribution of this thesis is the development of a novel SLAM solution capable of solving the SLAM problem in real time. This algorithm is called the Geometric Projection Filter or GPF. Rather than estimate the location of landmarks in global coordinates it estimates the relationships between individual landmarks. The convergence properties of this algorithm are derived and compared with those of the conventional AMF algorithm. An implementation of the GPF and the AMF is provided on a custom built subsea vehicle. The performance of the two filters are compared and shown to have the properties predicted by the preceding theoretical analysis. The authors claim that this implementation constitutes the fourth principal

contribution of the thesis. It shows that the GPF can be used as the basis of a substantive real time deployment of a mobile robot in an initially unknown environment.

Third, author claims that many problems still need to be solved before a mobile robot can provably operate in an entirely unknown environment and research continues on many fronts. Two approaches are of particular interest. First is an information theoretic formulation of the SLAM problem. Such a formulation may allow active sensing strategies to be developed that maximize the information content of the map or vehicle estimates. Secondly, the efficient and consistent use of sub maps may allow a 'divide and conquer' approach to be adopted in which landmark estimates are only manipulated in local regions of interest and hence allow computation to be significantly reduced. Many potential applications of SLAM require operation in natural, non-man made environments. The successful deployment of a robot in such an environment would constitute a general solution to the mobile robot navigation problem; however this remains an elusive goal. It requires the integration and co-ordination of four key competencies - natural landmark identification, data association, map management and the SLAM algorithm itself. Much successful research has been undertaken within each of these individual areas in isolation. The problem that must now be solved is how to fuse the algorithms and knowledge resulting from this endeavor into a system capable of robustly solving the navigation problem in real time. Until this fusion is accomplished, Simultaneous Localization and Map Building remains a challenging and fascinating problem.

This thesis was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2003. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. *International Joint Conference on Artificial Intelligence* 18, 1151–1156.

A Solution to the Simultaneous Localization and Map Building (SLAM) Problem

Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 2001. A solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, IEEE Transactions on* 17, 229–241.

First, reference in the article to previous work by Thrun, S., Fox, D., and Burgard, W. 1998. A probabilistic approach to concurrent mapping and localization for mobile robots. *Machine Learning*, 31.

Second, this article presents that the simultaneous localization and map building (SLAM) problem asks if it is possible for an autonomous vehicle to start in an unknown location in an unknown environment and then to incrementally build a map of this environment while simultaneously using this map to compute absolute vehicle location. Starting from the estimation-theoretic foundations of this problem, this paper proves that a solution to the SLAM problem is indeed possible. The underlying structure of the SLAM problem is first elucidated. The authors claim that a proof that the estimated map converges monotonically to a relative map with zero uncertainty is

then developed. It is then shown that the absolute accuracy of the map and the vehicle location reach a lower bound defined only by the initial vehicle uncertainty. Together, the authors claim that these results show that it is possible for an autonomous vehicle to start in an unknown location in an unknown environment and, using relative observations only, incrementally build a perfect map of the world and to compute simultaneously a bounded estimate of vehicle location. This paper also describes a substantial implementation of the SLAM algorithm on a vehicle operating in an outdoor environment using millimeter-wave (MMW) radar to provide relative map observations. The authors claim that this implementation is used to demonstrate how some key issues such as map management and data association can be handled in a practical environment. The results obtained are cross-compared with absolute locations of the map landmarks obtained by surveying. In conclusion, this paper discusses a number of key issues raised by the solution to the SLAM problem including suboptimal map-building algorithms and map management.

Third, the authors claim that this paper makes three principal contributions to the solution of the SLAM problem. First, it proves three key convergence properties of the full SLAM filter. Second, it elucidates the true structure of the SLAM problem and shows how this can be used in developing consistent SLAM algorithms. Finally, it demonstrates and evaluates the implementation of the full SLAM algorithm in an outdoor environment using a millimeter wave (MMW) radar sensor.

Finally, the authors claim that the implementation described in this paper is relatively small scale. It does, however, serve to illustrate a range of practical issues in landmark extraction, landmark initialization, data association, maintenance and validation of the SLAM algorithm. The authors claim that the implementation and deployment of a large-scale SLAM system, capable of vehicle localization and map building over large areas, will require further development of these practical issues as well as a solution to the map management problem. However, such a substantial deployment would represent a major step forward in the development of autonomous vehicle systems.

This thesis was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Mobile robot SLAM for line-based environment representation

Garulli, A., Giannitrapani, A., Rossi, A., and Vicino, A. 2005. Mobile robots SLAM for line-based environment representation. *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC '05. 44th IEEE Conference on*, 2041–2046.

First, this article addressed a problem that Simultaneous localization and map building (SLAM) is a challenging problem in mobile robotics that has attracted the interest of more and more researchers in the last decade. Self-localization of mobile robots is obviously a fundamental issue in autonomous navigation: a mobile robot must be able to estimate its position and orientation (pose) within a map of the environment it is navigating in. However, in many applications of practical relevance

(like exploration tasks or operations in hostile environments), a map is not available or it is highly uncertain. Therefore, in such cases the robot must use the measurements provided by its sensory equipment to estimate a map of the environment and, at the same time, to localize itself within the map.

Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 1999. A solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, IEEE Transactions on* 17, 229–241.

Second, this paper presents an algorithm for solving the simultaneous localization and map building (SLAM) problem, a key issue for autonomous navigation in unknown environments. The authors claim that the considered scenario is that of a mobile robot using range scans, provided by a 2D laser rangefinder, to update a map of the environment and simultaneously estimate its position and orientation within the map. The environment representation is based on linear features whose parameters are extracted from range scans, while the corresponding covariance matrices are computed from the statistical properties of the raw data. Simultaneous update of robot pose and linear feature estimates is performed via extended Kalman filtering. The authors claim that experimental tests performed within a real-world indoor environment demonstrate the effectiveness of the proposed SLAM technique.

Third, the authors claims that By adopting a line-based representation of the environment, the problem is cast as a state estimation problem and solved via extended Kalman filtering. The authors claim that the results of experimental validation, carried out using the mobile platform Pioneer 3AT, confirm the viability of the proposed approach in quite complex indoor environments.

Finally, the authors claim that future directions of research include the integration of additional features in the map (e.g., corners or point wise landmarks) and the comparison with different segmentation algorithms as well as with more sophisticated data association policies. The ability of the proposed SLAM technique to deal with large loops is a current subject of study. In this respect, the author claim that preliminary promising results have been obtained by simulation experiments. Moreover, the consistency of the line-based map in the long run is under investigation.

This thesis was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2003. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. *International Joint Conference on Artificial Intelligence* 18, 1151–1156.

Simultaneous Localization and Mapping with Sparse Extended Information Filters

Thrun, S., Liu, Y., Koller, D., Ng, A. Y., Ghahramani, Z., and Durrant-Whyte, H. 2003. Simultaneous localization and mapping with sparse extended information filters. *International Journal of Robotics Research* 23, 693–716.

First, this article addressed a problem that maintaining a Gaussian posterior imposes a significant burden on the memory and space requirements of the EKF. The

covariance matrix of the Gaussian posterior requires space quadratic in the size of the map, and the basic update algorithm for EKFs requires quadratic time per measurement update. This quadratic space and time requirement imposes severe scaling limitations. In practice, EKFs can only handle maps that contain a few hundred features. In many application domains, it is desirable to acquire maps that are orders of magnitude larger.

Bailey, T. 2001. Mobile robot localization and mapping in extensive outdoor environments. Ph.D. thesis, University of Sydney.

Second, this article proposed new algorithms which describe a scalable algorithm for the simultaneous mapping and localization (SLAM) problem. SLAM is the problem of acquiring a map of a static environment with a mobile robot. The vast majority of SLAM algorithms are based on the extended Kalman filter (EKF). In this paper they advocate an algorithm that relies on the dual of the EKF, the extended information filter (EIF).They show that when represented in the information form, map posteriors are dominated by a small number of links that tie together nearby features in the map. This insight is developed into a sparse variant of the EIF, called the sparse extended information filter (SEIF). SEIFs represent maps by graphical networks of features that are locally interconnected, where links represent relative information between pairs of nearby features, as well as information about the robot's pose relative to the map. They show that all essential update equations in SEIFs can be executed in constant time, irrespective of the size of the map. They also provide empirical results obtained for a benchmark data set collected in an outdoor environment, and using a multi-robot mapping simulation.

Finally, the authors claim that they have proposed an efficient algorithm for the SLAM problem. Their approach is based on the well-known information form of the EKF. Based on the empirical observation that the information matrix is dominated by a small number of entries that are found only between nearby features in the map, they have developed a SEIF. This filter enforces a sparse information matrix, which can be updated in constant time. In the linear SLAM case with known data association, all updates can be performed in constant time; in the nonlinear case, additional state estimates are needed that are not part of the regular information form of the EKF. They have proposed an amortized constant-time coordinate descent algorithm for recovering these state estimates from the information form. They have also proposed an efficient algorithm for data association in SEIFs that requires logarithmic time, assuming that the search for nearby features is implemented by an efficient search tree. The approach has been implemented and compared to the EKF solution. Overall, they find that SEIFs produce results that differ only marginally from that of the EKFs, yet at a much improved computational speed. Given the computational advantages of SEIFs over EKFs, they believe that SEIFs should be a viable alternative to EKF solutions when building high-dimensional maps.

This thesis was cited by Dissanayake, G., Durrant-Whyte, H., and Bailey, T. 2000. A computationally efficient solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on* 2, 1009–1014.

Analysis of Positioning Uncertainty in Simultaneous Localization and Mapping (SLAM)

Mourikis, A. I. and Roumeliotis, S. I. 2004. Analysis of positioning uncertainty in simultaneous localization and mapping (slam). *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* 1, 13–20.

First, this article addressed a problem that the main limitation of maintaining all the cross correlation elements of the covariance matrix in EKF based SLAM is that it results in algorithms which have complexity quadratic in the number of features. This leads to a prohibitively large computational load in cases when online estimation of a large map is necessary.

Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 1999. A solution to the simultaneous localization and map building (slam) problem. Robotics and Automation, IEEE Transactions on 17, 229–241.

Second, this article studies the time evolution of the covariance of the position estimates in single-robot Simultaneous Localization and Mapping (SLAM). The authors claim that a closed-form expression is derived, that establishes a functional relation between the noise parameters of the robot's proprioceptive and exteroceptive sensors, the number of features being mapped, and the attainable accuracy of SLAM. Furthermore, the authors claim that it is demonstrated how prior information about the spatial density of landmarks can be utilized in order to compute a tight upper bound on the expected covariance of the positioning errors. The derived closed-form expmsions enable the prediction of SLAM positioning performance, without resorting lo extensive simulations, and thus offer an analytical tool for determining the sensor characteristics required to achieve a desired degree of accuracy. The authors claim that simulation experiments are conducted, that corroborate the presented theoretical analysis.

Finally, the authors claim that they have presented a method for predicting the positioning performance in SLAM, without the need to resort to extensive simulations or experimentation. This was achieved through a theoretical study of the time evolution of the position estimates' covariance, that allowed for the derivation of an analytical upper bound for the positioning uncertainty. The closed-form expression establishes a functional relation between the noise parameters of the robot's sensors, the number of features being mapped, and the accuracy of SLAM. Moreover, when prior information, in the form of a model for the density of landmarks in the area, is available, they can determine a tighter upper hound for the expected value of the steady state covariance of the errors for both the robot and the map features. Thus, a powerful design tool is made available that enables the prediction of the performance of a robot in a mapping application. This can he employed to determine the required accuracy of the robot's sensors, in order to meet task-dependent specifications. Certainly, the authors claim that the most restrictive assumption employed in the current work is that the robot can see all landmarks simultaneously. The authors claim that although this is not possible in most real-world applications, the presented analysis can serve as a basis for extensions to more realistic scenarios, where only

subsets of the map are visible at each time instant.

This thesis was cited by Montemerlo, M. and Thrun, S. 2003. Simultaneous localization and mapping with unknown data association using fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 2, 1985–1991.

Interactive SLAM using Laser and Advanced Sonar

Diosi, A., Taylor, G., and Kleeman, L. 2005. Interactive slam using laser and advanced sonar. *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, 1103–1108.

First, this article addressed a problem that Most practical applications of mobile robotics require the robot to travel autonomously between multiple locations, typically requiring the robot to localize itself within a map of the environment. Map building is therefore a fundamental problem for which a variety of solutions have been used in previous work, including measurement by hand, interactive guidance with manual control or people following, and autonomous exploration. Manual map building is time-consuming and usually not considered a practical solution for robots required to operate in different environments.

Althaus, P., and Christensen, H. I. 2003. Automatic map acquisition for navigation in domestic environments. In Proc. ICRA.

Second, this article proposed a novel approach to mapping for mobile robots that exploits user interaction to semi autonomously create a labeled map of the environment. The robot autonomously follows the user and is provided with a verbal commentary on the current location with phrases such as "Robot, we are in the office". At the same time, a metric feature map is generated using fusion of laser and advanced sonar measurements in a Kalman filter based SLAM framework, which is later used for localization. When mapping is complete, the robot generates an occupancy grid for use in global task planning. The occupancy grid is created using a novel laser scan registration scheme that relies on storing the path of the robot along with associated local SLAM features during mapping, and later recovering the path by matching the associated local features to the final SLAM map. The occupancy grid is segmented into labeled rooms using an algorithm based on watershed segmentation and integration of the verbal commentary. The authors claim that experimental results demonstrate their mobile robot creating SLAM and segmented occupancy grid maps of rooms along a 70 meter corridor, and then using these maps to navigate between rooms.

Third, the authors claim that they have presented an interactive framework that enables a robot to generate a segmented metric map of an environment by following a tour guide and storing virtual markers created through verbal commands. Throughout the mapping process, the robot performs Kalman filter based SLAM using a fusion of advanced sonar and laser measurements. Two maps are generated at the completion of the mapping process: a SLAM map consisting of point and line features used for

localization, and an occupancy grid for task planning. Generation of an accurate occupancy grid is central to their framework, and has been addressed with the development of a novel technique for laser scan registration. During mapping, the location of the robot and an associated laser scan are periodically recorded, along with several local features in the current SLAM map. The path of the robot can be recovered later by matching the stored local features to points in the final SLAM map using a modification of the laser scan matching algorithm. An occupancy grid consistent with the SLAM map is recovered by overlaying the laser scans on the corrected robot path. The authors claim that experimental results have demonstrated the necessity of path correction, and verify that their approach generates accurate occupancy grids. This paper has also introduced a novel method for interactive segmentation of the occupancy grid, based on the watershed algorithm with an additional merging stage guided by the verbally generated markers. The authors claim that this approach was successfully demonstrated to segment the map of an office environment into six labeled regions. The segmented map was used to plan a path between rooms, but knowledge of the extent of free space in each room could also be utilized for tasks such as floor cleaning.

Finally, the authors claim that in future work, they intend to extend the system by implementing large loop-closing, and a global localization strategy to determine the pose of the robot anywhere in the SLAM map. Furthermore, visual sensing could lead to a number of improvements by providing additional features for both SLAM and person following. Their recent work in multiple hypothesis laser-based people tracking could also lead to improved people following behavior.

This thesis was cited by Kruijff, G. M., Zender, H., Jensfelt, P. and Christensen, H. I., 2006. Clarification dialogues in human-augmented mapping. *Proceeding of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction HRI '06*, 282–289.

SmartSLAM: localization and mapping across multi environment

Asmar, D. C., Zelek, J. S., and Abdallah, S. M. 2004. Smartslam: localization and mapping across multi-environments. *Systems, Man and Cybernetics, 2004 IEEE International Conference on* 6, 5240–5245.

First, this article addressed a problem that in the obscene of absolute localization tools such as GPS, robot can still successfully navigate by conducting Simultaneous Localization and Mapping (SLAM). All SLAM algorithms date can only be applied in one environment at a time.

Guivant, J. and Nebot, E. June 2001. Optimization of the simultaneous localization and map building algorithm for real time implementation. *IEEE Transaction of Robotic and Automation.*

Second, the authors claim that they propose to extend SLAM to multi-environments. In SmartSLAM, the robot first classifies its entourage using environment recognition code and then performs SLAM using landmarks that are appropriate for its surrounding milieu. The authors claim that one thousand images of various indoor and

outdoor environments were collected and used as training data for a three-layered feed forward back propagation neural meshwork. This neural network was then tested on two sets of query images of indoor environments and another two sets of outdoor environments, yielding 83% and 95% correct classification rules for the indoor images and 80% and 79% success rates for the outdoor images.

Third, the authors also claim that the contribution of this paper is twofold. Firstly, this is the first algorithm that performs SLAM across multi environments. SmartSLAM uses environment recognition as a primer for feature selection. The second contribution of this paper is in the area of environment recognition and classification. SmartSLAM classifies images using learning alone. A neural network is trained to classify indoor and outdoor environments

Finally, future work will include a more comprehensive list of environments and investigate a methodology for feature representation and selection.

This thesis was cited by Dissanayake, G., Durrant-Whyte, H., and Bailey, T. 2000. A computationally efficient solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on* 2, 1009–1014.

Sequential 3D-SLAM for mobile action planning

Kohlhepp, P., Pozzo, P., Walther, M., and Dillmann, R. 2004. Sequential 3d-slam for mobile action planning. *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* 1, 722–729.

First, this article addressed a problem that the inspection of thermally or chemically stressed parts in process plants, supported by infrared thermograph, is an important application for future freely navigating mobile robots. Understanding and comparing the infrared images requires precise spatial alignment and the surface geometry to be known. Objects that are routinely examined must be recognized and relocated. These tasks require truly three dimensional environment maps. A similar problem arises in surveying and condition monitoring hardly accessible environments. In such areas of poor illumination, active optical sensors (laser scanners) lend themselves for environment capture despite their higher cost and lower resolution as compared to video cameras.

Thrun, S., Fox, D., and Burgard, W. 1998. A probabilistic approach to concurrent mapping and localization for mobile robots. *Machine Learning*, 31.

Second, the authors claim that reliable mapping and self-localization in three dimensions while moving is essential to survey inaccessible work spaces or to inspect technical plants autonomously. Their solution to this 3D SLAM problem is novel in several respects. First a new rotating laser-scanning setup is presented for acquiring point clouds and reducing them to surface patches in real time. Second, the SLAM algorithms work entirety on highly reduced, attributed surface models and in 3D.

Third, The authors claim that they propose a novel system architecture of an Extended Kalmam filter (EKF) for 3D position tracking, cooperating with a 3D range

image understanding system for matching, aligning, and integrating overlapping range views. The system is demonstrated by an indoor exploration tour.

Fourth, the authors also claim that they presented a new SLAM system concept working entirely in 3D and with attributed surface models. A novel rotating laser scanner RoSi continuously captures dense, foveal range views which are reduced to surface patches exploiting the Moebius band parameter space topology. For sequential map building, an EKF provides coarse pose estimation from navigation sensors while range image object recognition and locating system provides precise alignment of overlapping range views. Both subsystems propagate their pose uncertainties individually. The navigation based uncertainty effectively restricts the search space of the RRT, and the map based uncertainty in turn resets the EKF estimates. Preliminary results from a small office exploration tour indicate that the crude surface maps produced are accurate and adequate for mobile action planning. One next step will be to extract generalized cylinder surfaces for plant exploration.

Finally, the authors claim that the global pose correction not covered in this article is ongoing research. An elastic graph having as its nodes a limited number of overlapping sub maps with time-varying poses is the key concept to identify and correctly close cycles in the work space, and to propagate global pose corrections over the network.

This thesis was cited by Montemerlo, M. and Thrun, S. 2003. Simultaneous localization and mapping with unknown data association using fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 2, 1985–1991.

Combinatorial maps for Simultaneous Localization and Map building (SLAM)

Dufourd, D., Chatila, R., and Luzeaux, D. 2004. Combinatorial maps for simultaneous localization and map building (slam). *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, 1047–1052.

First, this article addressed a problem that the simultaneous localization and map building (SLAM) problem has been widely studied in the robotics community since the ability to construct environment models appears as a key to autonomy for mobile robots. Recent publications underline the need for high-level models that would combine different representation modes, possibly attaching semantic information. Such models would be required to develop more sophisticated planning algorithms and to perform efficient global reasoning.

Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 1999. A solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, IEEE Transactions on* 17, 229–241.

Second, the authors claim that in this article they focus on environment models for the well-known Simultaneous Localization and Map building (SLAM) problem, which has received considerable attention in the robotics community over the past few years. First, they compare different existing map representations to discuss their

advantages and limitations in the scope of indoor robotics applications. Then they define a highly structured map model which combines different kind of representations, including space-based, grid-based as well as Feature based formats. This model also provides topological information such as adjacency links, which are similar to the topological layer used in geographical information systems. They explain how to build and update map according to this model, using a mobile robot equipped with a laser scanner and underline how the structure of their representation may increase robustness in a Kalman-based SLAM process. Finally, they show same preliminary experiments and propose A few perspectives for this Work.

Third, the authors also claim that they have defined a highly structured and consistent map model for SLAM which combines different representation modes: frontier-based, space-based, grid based and topological (in the sense that it contains all adjacency links), they have also explained how to build indoor maps according to this model using an EKF framework maintaining all cross-correlation parameters. The high-level structure of the model induces more complex processing to build the map but in return, it is likely to improve SLAM robustness and provides useful information for global spatial reasoning and planning. Moreover, the similarities with geographical models offer several advantages: GIS classical queries could be transposed to robotics applications and GIs manipulation operations could be used to manage the maps built by robots. In the future, we can even imagine robotic vehicles which would complete existing GIS outdoor maps with their own indoor maps in an autonomous way. The authors claim that the preliminary experiments are encouraging although they need more extensive tests to validate their system.

This thesis was cited by Montemerlo, M., Thrun, S., Koller, D., and Wegbreit, B. 2002. Fastslam: A factored solution to the simultaneous localization and mapping problem. *Proceedings of the National Conference on Artificial Intelligence*, 593–598.

Year	Ref.	Title of Paper	Major Contribution
2000	Dissanayake, M. W. M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., and Csorba, M. 2000. A solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, IEEE Transactions on* 17, 229–241.	A Solution to the Simultaneous Localization and Map Building (SLAM) Problem	First, it proves three key convergence properties of the full SLAM filter. Second, it elucidates the true structure of the SLAM problem and shows how this can be used in developing consistent SLAM algorithms. Finally, it demonstrates and evaluates the implementation of the full SLAM algorithm in an outdoor environment using a millimeter wave (MMW) radar sensor.
2000	Dissanayake, G., Durrant-Whyte, H., and Bailey, T. 2000. A computationally efficient solution to the simultaneous localization and map building (slam) problem. *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on* 2, 1009–1014.	A Computationally Efficient Solution to the Simultaneous Localization and Map Building (SLAM) Problem	The key contribution of this paper is a map management strategy that results in a computationally efficient solution to SLAM.
2000	Thrun, S., Liu, Y., Koller, D., Ng, A. Y., Ghahramani, Z., and Durrant-Whyte, H. 2000. Simultaneous localization and mapping with sparse extended information filters. *International Journal of Robotics Research* 23, 693–716.	Simultaneous Localization and Mapping with Sparse Extended Information Filters	This article proposed new algorithms which describe a scalable algorithm for the simultaneous mapping and localization (SLAM) problem.
2001	Guivant, J. and Nebot, E. June 2001. Optimization of the simultaneous localization and map building algorithm for real time implementation. *IEEE Transaction of Robotic and Automation*, 318-325.	Optimization of the Simultaneous Localization and Map-Building Algorithm for Real-Time Implementation	This article addresses real-time implementation of the simultaneous localization and map-building (SLAM) algorithm.

2004	Mourikis, A. I. and Roumeliotis, S. I. 2004. Analysis of positioning uncertainty in simultaneous localization and mapping (slam). *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* 1, 13–20.	Analysis of Positioning Uncertainty in Simultaneous Localization and Mapping (SLAM)	They have presented a method for predicting the positioning performance in SLAM, without the need to resort to extensive simulations or experimentation.
2004	Diosi, A., Taylor, G., and Kleeman, L. 2004. Interactive slam using laser and advanced sonar. *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, 1103–1108.	Interactive SLAM using Laser and Advanced Sonar	This article proposed a novel approach to mapping for mobile robots that exploits user interaction to semi autonomously create a labeled map of the environment.
2004	Dufourd, D., Chatila, R., and Luzeaux, D. 2004. Combinatorial maps for simultaneous localization and map building (slam). *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, 1047–1052.	Combinatorial maps for Simultaneous Localization and Map building (SLAM)	They have defined a highly structured and consistent map model for SLAM which combines different representation modes: frontier-based, space-based, grid based and topological (in the sense that it contains all adjacency links), they have also explained how to build indoor maps according to this model using an EKF framework maintaining all cross-correlation parameters.
2004	Asmar, D. C., Zelek, J. S., and Abdallah, S. M. 2004. Smartslam: localization and mapping across multi-environments. *Systems, Man and Cybernetics, 2004 IEEE International Conference on* 6, 5240–5245.	SmartSLAM: localization and mapping across multi environment	Firstly, this is the first algorithm that performs SLAM across multi environments. SmartSLAM uses environment recognition as a primer for feature selection. The second contribution of this paper is in the area of environment recognition and classification.

2004	Kohlhepp, P., Pozzo, P., Walther, M., and Dillmann, R. 2004. Sequential 3d-slam for mobile action planning. *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on* 1, 722–729.	Sequential 3D-SLAM for mobile action planning	They propose a novel system architecture of an Extended Kalmam filter (EKF) for 3D position tracking, cooperating with a 3D range image understanding system for matching, aligning, and integrating overlapping range views.
2005	Garulli, A., Giannitrapani, A., Rossi, A., and Vicino, A. 2005. Mobile robots SLAM for line-based environment representation. *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC '05. 44th IEEE Conference on*, 2041–2046.	Mobile robot SLAM for line-based environment representation	This paper presents an algorithm for solving the simultaneous localization and map building (SLAM) problem, a key issue for autonomous navigation in unknown environments.

Year	Ref.	Title of Paper	Major Contribution
2003	Montemerlo, M. and Thrun, S. 2003. Simultaneous localization and mapping with unknown data association using fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 2, 1985–1991.	Simultaneous localization and mapping with unknown data association using FastSLAM	This article proposed new algorithms which show that FastSLAM also substantially outperforms the EKF in environments with ambiguous data association.
2003	Nieto, J., Guivant, J., Nebot, E., and Thrun, S. 2003. Real time data association for fastslam. *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on* 1, 412–418.	Real Time Data Association for FastSLAM	This article proposed new algorithm a real-world implementation of FastSLAM, an algorithm that recursively estimates the full posterior distribution of both robot pose and landmark locations.
2003	Hahnel, D., Burgard, W., Fox, D., and Thrun, S. 2003. An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on* 1, 206–211.	An Efficient FastSLAM Algorithm for Generating Maps of Large-Scale Cyclic Environments from Raw Laser Range Measurements	This article proposed new algorithm which combines Rao-Blackwellized particle filtering and scan matching.
2004	Cyrill, S., Dirk, H., and Wolfram, B., 2004. Exploration with Active Loop-Closing for FastSLAM. *Proceedings of 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 1505–1510	Exploration with Active Loop-Closing for FastSLAM	This article proposed new algorithm that a novel and integrated approach combines autonomous exploration with simultaneous localization and mapping.

2006	Bailey, T., Nieto, J., and Nebot, E., 2006. Consistency of the FastSLAM Algorithm. *Proceedings of 2006 IEEE International Conference on Robotics and Automation*, 424–429.	Consistency of the FastSLAM Algorithm	This article presents an analysis of FastSLAM a Rao-Blackwellized particle filter formulation of simultaneous localization and mapping.