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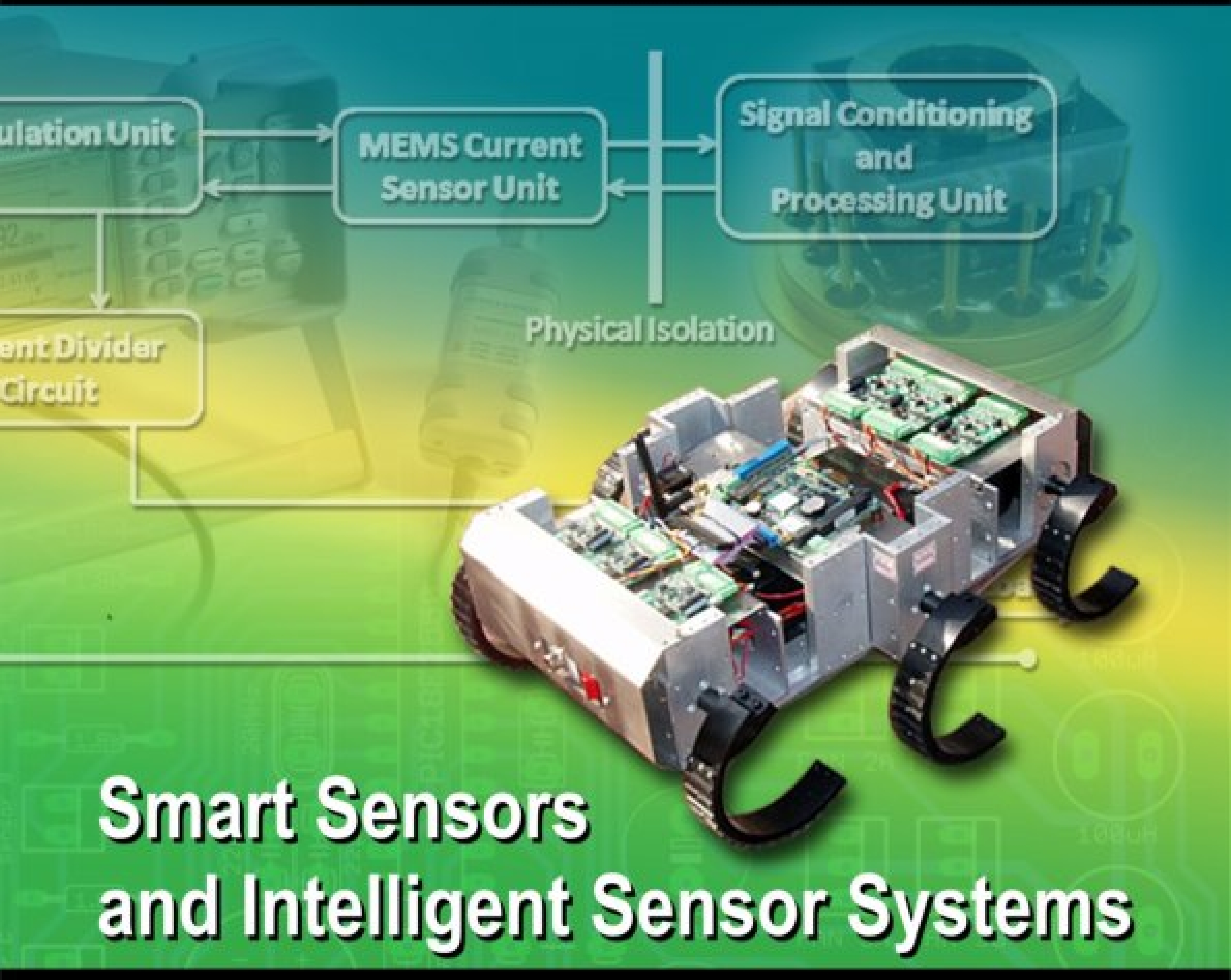

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Stochastic Filters for Mobile Robot SLAM Problems - A Review

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Abstract: Simultaneous Localization and Mapping (SLAM) is a challenging area of research in robotics domain. Implementation of SLAM using stochastic filters has been an interesting area of research for the past two decades. The aim of this paper is to provide a comprehensive review of the research work done on stochastic filters based approaches in SLAM problem. The effectiveness and computational issues of these filters are examined. The limiting factors associated with these probabilistic filters identified from various literatures in this domain are addressed. In addition the scope of further research work in the area of SLAM is being highlighted. *Copyright © 2012 IFSA.*

Keywords: SLAM, EKF, Particle filter

1. Introduction

When there is a restriction on use of external sensors such as Global Positioning System (GPS) localization of the Autonomous Mobile Robot (AMR) in an unknown environment becomes very challenging. The robot is left to localize itself based on the data from the onboard sensors and relative to the features seen while exploring the environment. This problem of simultaneously constructing a map of an environment amidst uncertain pose of a mobile robot as well as estimating the pose amidst changing environment is referred to as the simultaneous localization and mapping (SLAM). This mutual relation between the pose and the map estimates makes the SLAM problem difficult as the information gathered through various local sensors are uncertain due to sensor noise, time bound deformity in the physical structure of mobile robot and ambience of the environment. Since large amount of uncertainty prevails in the sensor data, linear filters can seldom be used. So in order to estimate the current state of the robot, decision may be taken based on fresh observations of the same environment. This paves the path for probabilistic and statistical based stochastic filters. In the past two decades many researchers have contributed richly in this domain. Every time a measurement is made the belief factor on the estimate is improved. Thus the estimates are updated by fresh measurements, which normally will refine the original estimate removing the uncertainty. The filtering approach for this problem comes under two main categories and they are Kalman filters and particle filters. These filters are generally called as online SLAM algorithms.

Smith, Self and Cheeseman [1] in 1990 developed a path breaking approach of applying Extended Kalman Filter (EKF) as a stochastic estimating tool for SLAM. The mathematical foundation related to the veracity of a stochastic solution in estimating concurrently both the robot pose and the map was proved using EKF as a filtering tool in this work. They have established the idea of correlation between the estimates of not only the robot's pose but as well as between the map features and they have proved that the correlation gets strengthened with every new observation using sensors. This seminal paper has opened up a new area of research in addressing SLAM problem because till that time mapping and localization were viewed as two different problems and cannot be addressed simultaneously. Though there were a number of practical implementations of EKF as a SLAM tool [2,3] after the initial work done by Smith et al, the research community started to probe deeper into the shortcomings of EKF. The limitation was identified to fall under three broad categories such as computational complexity, estimation accuracy due to linearization errors and data associations. When the area of the map to be explored was small (less than 100 mts) EKF based SLAM gave appreciable results and when the map area increases the size of the co-variance matrix in EKF also increases phenomenally, making computation very difficult. When observed features in a map are distinct then data association of the information from the sensors on to the features are unique. But when identical features are observed and are very close to each other then data association itself becomes a challenging problem. The computational complexity issues associated with more number of features was solved by Thrun et al [4] using sparse information filter [SIF]. In the quest for addressing the linearization error problems with EKF as well as to reduce the computational burden the idea of Monto-carlo based particle filters was considered [5]. The problem with EKF is, it cannot represent the real probability distributions effectively using the first and second statistical moments. But a particle filter with the help of random samples can approximate the posterior probabilistic density function effectively. Montemerlo et al [6,7] came up with two algorithms using particle filters for solving the SLAM problem and they are popularly called as FastSLAM algorithms. In order to address the linearization problem recently Unscented Kalman filter (UKF) based solution was also tried with reduced computational requirements [8]. In addition to these methods the problem associated with SLAM has propelled the research community over the past decade to come up with many novel versions of these algorithms.

The objective of this paper is to review, give a comprehensive picture of SLAM problem and to highlight some of the recent trends of these stochastic filtering algorithms and conclude with discussing some of the cutting edge research directions in this domain.

This paper is organized as follows. Section II gives a comprehensive view about the SLAM problem. The extended Kalman filter based SLAM and its related advanced versions are discussed in Section III. The implementation issues and the algorithmic novelties associated with particle filters are addressed in detail in Section IV. The paper is concluded with a focus on future directions in SLAM.

2. SLAM Problem

The process of constructing a map of an unknown environment based on the landmark features as well as estimating the pose of the mobile robot with respect to the environment is referred to as the simultaneous localization and mapping (SLAM).

To illustrate the SLAM problem let us consider the Fig. 1. which shows various landmarks in the map as ‘ m_j ’, the robot states as ‘ x_k ’ and the control drive given to the robot as u_k .

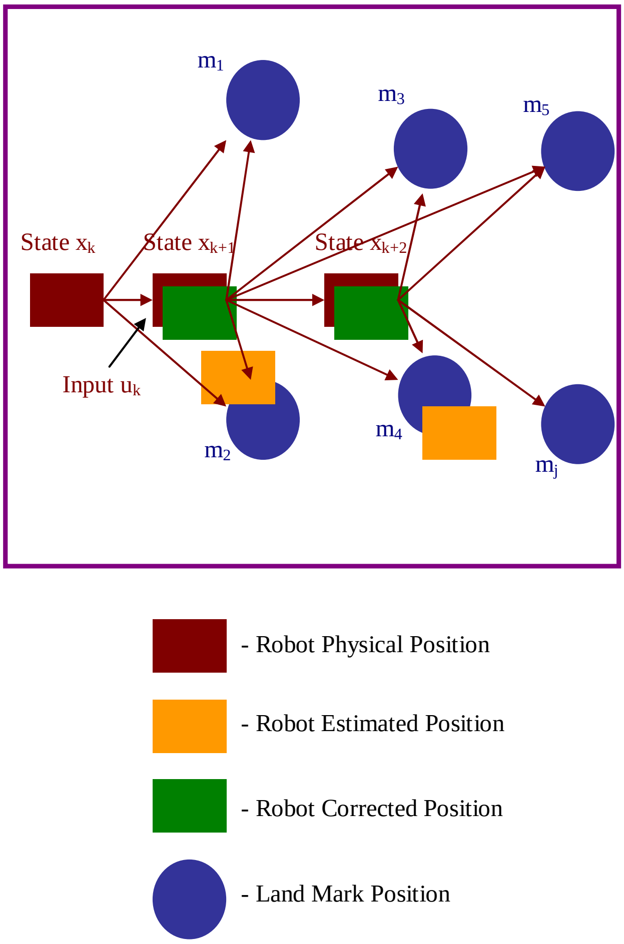

Fig. 1. Pictorial representation for SLAM problem.

The robot obtains the location of the landmarks through the onboard sensors. The belief factor on these locations during the first observation is assumed to be the maximum. Once the location of the visible landmarks are obtained from position x_k (the mapping problem) depending up on u_k the next possible state x_{k+1} of the robot is estimated. Then the range and bearing of the landmarks viewed at x_k is estimated from x_{k+1}. To refine the estimate a new re-observation is made once the robot physically moves to x_{k+1} (localization problem). This process is repeated for the entire mapping and localization process.

The above process is being illustrated mathematically below in equations 1, 2, 3, and 4

The current state of the system is

$$s_k = f(x_k, m_k) \tag{1}$$

Note: The system model involves both robot and the map at any point of time.

The current robot state is

$$x_k = f(x_{k-1}, u_k, \upsilon_k) \tag{2}$$

The landmark state is

$$m_k = f(m_{k-1}) \tag{3}$$

The observation made at any instant of time is

$$y_k = f(x_k, m_k, \omega_k) \tag{4}$$

s_k is the state estimates and y_k is the observation made at each instant of time.

υ_k & ω_k are the process noise and measurement noise respectively which is generally assumed to be totally uncorrelated and zero mean Gaussian noise.

The uncertainties depicted in the form of noise covariance matrices associated with both the robot pose and the sensor data is recursively updated at each time step using online SLAM algorithm which are elaborated in the following sections.

3. EKF SLAM

The basic idea behind Kalman filter stems from the linear least square solutions formulated by Gauss during the year 1805. Kalman published the seminal paper on recursive least square algorithm as an estimation tool for linear control system problem in the year 1960 [9, 10]. Kalman filter as an estimation tool for mobile robot SLAM problem was implemented during 1990 [1]. In this work Kalman filter is applied for solving non-linear estimation problems using first order Taylor series approximation and it is popularly called as EKF. It is found from literature that the family of Kalman filters has been employed extensively in addressing the SLAM problem [9]. The importance of EKF as a foundational tool in solving the SLAM problem is emphasized clearly in the two significant recent survey papers [9, 11]. EKF SLAM usually work with a state vector comprises of the robot's pose and landmark feature's position. The online algorithm will eventually estimate the uncertainties involved in the robot's pose and feature's location. The complete posterior correlation between the robot location and landmark map can be generated effectively using EKF. However when the number of features increases it creates huge computational burden, leading to poor real time estimation. For example for a 2D SLAM problem there will be 2N+3 states involved in the computation in any instant of time and the Covariance matrix will hold (2N +3) x (2N+3) elements and when N increases it leads to a quadratic increase in storage requirements as well as the computing time taken for each update of this matrix. This leads to a condition that full covariance matrix based EKF can be applied in real time to small maps (reduced number of landmarks) and reduced sensor update rates. The problem associated with this constraint is well analyzed in [12, 13]. To provide solution to this problem an innovative method of using the inverse of the covariance matrix is given [14]. This inverse matrix is called generally as information matrix and it is identified to be sparse in nature. So eventually the computational burden got significantly reduced. This algorithm was made more efficient by the calculation of the error bounds which is investigated in [15].

The sparse nature of the information matrix can also be generated by including both features and a sequence of robot poses in the state vector as discussed in [16, 17]. To reduce the computational burden an innovative SLAM with state vector containing only robot poses is proposed in [18] and this technique is known as Exactly Sparse Delayed state filter (ESDF). Wang et al [19] proposed a novel D-SLAM technique using the SIF but without using the previous robot poses in the state vector. In the similar fashion Walter et al [20] came out Exactly Sparse extended information filter (ESEIF). Though sparse nature of these algorithms reduces the computational burden, it increases the complexity of the recovery of the relevant elements in the information matrix as required in the data association stage. This process increases the computational cost. A comparative study on these information matrix filters are found in [21] and it is stated that DSLAM was consistent, information loss is less, memory demand is less and data association is more exact.

In order to implement effectively the EKF in a real time environment both the nonlinear robot model and the observation model should be reasonably accurate. These models can be incorporated in the online algorithm using various linearizing approximation techniques, which leads to errors in both landmark and robot pose estimation. These errors in turn lead to imprecise covariance matrix. The effect of this problem is studied in detail in [22]. Moreover sensor bias also cripples the performance of EKF to a large extent and recently researchers are addressing this problem using some novel sensor bias estimation algorithms [23, 24, 25].

The problems related to EKF are also approached from different modified versions of Kalman filters. Most notably it is observed from literature that the UKF as a tool for SLAM and its implementation issues are investigated in [26, 27]. An unscented transformation is more related to particle filters where in the probability distribution functions (pdf) are sampled randomly. But in UKF it is done through careful selection of deterministic sigma points in order to maintain the moments of the distribution. In spite of the superiority of Unscented Kalman filter over EKF both these methods are basically affected by inconsistency problem. But it is also observed that by applying the UKF only to the robot’s states will results in more accurate covariance estimates and a more computationally efficient nonlinear transformation [26]. However, this technique is restricted only where the system and sensor noises are assumed to be Gaussian in nature.

Guivant [28] introduced a novel method of compressed EKF (CEKF) with an objective of improving the computational requirements of EKF-SLAM in large environments. Zhou et al [29] proposed the mean extended Kalman filter (MEKF) with a similar interest in reducing the computational burden of EKF. It is proved through simulation that the MEKF is computationally efficient. A comparative study of these families of Kalman filters was done using simulation and the results are published in [30]. The simulation work in this paper was carried out to compare the non iterated Sigma Point Kalman filter (SPKF) and EKF with their corresponding iterated versions and gives the comparative performance of these various versions of Kalman filters. It was inferred that iterated versions of both EKF and SPKF shows much reduced mean square error, normalized estimation squared error (NEES) and reduced computational time. The experimental details are explained well in [30]. The results that come out of these studies are to be validated in the real time environment with more field trials.

4. Particle Filter Based FastSLAM

EKF can estimate a fully correlated posterior over landmark maps and robot poses. But their weakness lies in the assumptions and approximations that have to be made on the robot motion model and sensor noise. Rao-Blackwellized particle filter (RBPF) has become an effective tool in solving SLAM problem. Particle filter represent distributions using a finite set of sample states or “particles”. It is identified from literature that RBPF is confined to problems of lower dimensionality. Initially it was believed that particle filters are especially ill suited to the SLAM problem which is a higher dimensional problem. However this idea was disproved when Murphy et al [31] proposed the (RBPF) for solving the SLAM problem. Each particle in this method denotes a possible choice of the trajectory of the mobile robot and a map of the environment. In [31] it is stated that the SLAM posterior can be factored into a product of a robot path posterior and N landmark posterior conditioned on the robot's path. The robot path posterior is of low dimensionality and can be estimated efficiently using a particle filter.

The factorization idea proposed in [31] was immediately developed by Montemerlo et al [32, 33] for SLAM problems. In this paper they called the algorithm as FastSLAM. In [32] it is shown that the full SLAM posterior can be approximated using FastSLAM algorithm. The derivation of this algorithm works on three basic premises: particle filters, conditional dependence and resampling. FastSLAM algorithm innovatively employs and integrates both particle filter and extended Kalman filter. The resampling process accounts for the difference of the target and the proposal distribution. In [34] a novel approach of grid based version of FastSLAM was introduced. In order to improve the efficiency of learning the grid maps Eliazar et al [35] proposed an efficient map representation. FastSLAM 2.0 [36] is an improved version of FastSLAM 1.0 and it takes fresh measurement also into account when the proposal distribution is made. This is done by sampling poses based on the measurement in addition to the control signal. Grisetti et al [37] proposed an extension of the approach wherein instead of using a fixed proposal distribution their algorithm computes an improved proposal distribution on a per-particle basis.Rodriguez et al proposed a Dual FastSLAM algorithm which is basically a dual of FastSLAM 1 relying more on the accuracy of the feature based sensors and the mean square error and computational performance are compared with FastSLAM 1 and 2 [38]. It has been concluded that the robot pose mean square error, processing time, and particle diversity substantially improved in Dual FastSLAM.

5. Discussions & Future Directions

The research work on SLAM has seen lot of advancement for the past two decades. Most of the work on SLAM is based on EKF and particle filters. Still the problem of uncertainty persists and remains to be addressed as its keeps accumulating leading to an upper bound when the exploration time is more for a robot. This may also lead to loop closing problem ie when the robot revisits an area after some time gap, it may not be able to correlate or identify the features. Lot of assumptions and linearization makes the consistency of SLAM algorithm a questionable issue.

Some of the future directions on SLAM research involves: 1. Large scale implementation like highly chaotic and multi terrain environment with large number of features. This emphasize the use of 3D SLAM which makes the problem complex by means of computational speed and memory capacity thus making it highly challenging. 2. To investigate deeper into dynamic SLAM 3. Cooperative SLAM (CSLAM) based on minimum onboard sensors and deploying a team of robot to work in an interoperable cooperative fashion towards reaching the desired goals.

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Guide for Contributors

Aims and Scope

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- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
- Signal processing;
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- Nanosensors;
- Microsystems;
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