Robust SVSF-SLAM for Unmanned Vehicle in Unknown Environment

Article · December 2016

DOI: 10.1016/j.ifacol.2016.10.585

Abdelkrim NEMRA
Ecole Militaire Polytechnique

Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-21 (2016) 386–394

Robust SVSF-SLAM for Unmanned Vehicle in Unknown Environment

Fethi DEMIM * **Abdelkrim NEMRA** ** **Kahina LOUADJ** ***

* *Laboratoire Robotique et Productique à l'U.E.R Automatique, Ecole Militaire Polytechnique, Bordj El Bahri,BP 17, 16111, Algiers. Algeria. (email:demifethi@gmail.com).*

** *Laboratoire Robotique et Productique à l'U.E.R Automatique, Ecole Militaire Polytechnique, Bordj El Bahri,BP 17, 16111, Algiers. Algeria. (email: karim_nemra@yahoo.fr)*

*** *Laboratoire d'Informatique, de Mathématiques , et de Physique pour l'Agriculture et les Forêts (LIMPAF). Université de Bouira. Algeria. (email:louadj_kahina@yahoo.fr)*

Abstract: Simultaneous localization and mapping (SLAM) is an important topic in the autonomous mobile robot research. The most popular solutions of this problem are the EKF-SLAM and the FAST-SLAM, the former requires an accurate process and observation model and suffer from the linearization problem, and the latter is not suitable for real time implementation. Therefore, a new alternative solution based on the smooth variable structure filter (SVSF-SLAM) algorithm is proposed in this paper to solve the Unmanned Ground Vehicle (UGV) SLAM problem. The SVSF filter which is formulated in a predictor-corrector format is robust face parameters uncertainties and error modeling and doesn't require any assumption about noise characteristics. In this paper the SVSF-SLAM algorithm is implemented using the odometer and LASER data to construct a map of the environment and localize the UGV within this map. The proposed algorithm is validated and compared to the EKF-SLAM algorithm. Good results are obtained by the SVSF-SLAM comparing to the EKF-SLAM especially when the noise is colored or affected by a variable bias. Which confirm the efficiency of our approaches.

Keywords: localization; mapping; feature extraction; data association; EKF-SVSF filters; mobile robot.

1. INTRODUCTION

Simultaneous localization and mapping (SLAM) is the process that enables a mobile robot to localize and build a map of an unknown environment using only observations relative to the most relevant features detected by its sensors. SLAM is an essential capability for our UGV traveling in unknown environments where globally accurate position data (e.g. GPS) is not available. In particular, mobiles robots have shown significant promise for remote exploration, going places that are too distant [1], too dangerous [2], or simply too costly to allow human access. If robots are to operate autonomously in extern environment undersea, underground, and on the surfaces of other planets, they must be capable of building maps and navigating reliably according to these maps. The solution to the SLAM problem is considered by many as a key prerequisite for making a robot fully autonomous [3] [4]. This problem has been the object of significant research in the last decade. The problem of SLAM has attracted immense attention in the robotics literature. SLAM addresses the problem of a mobile robot moving through an environment of which no map is available a priori. The robot makes relative observations of its ego-motion and of features in its environment, both corrupted by noise. The goal of SLAM is to reconstruct a map of the world and the path taken by the robot.

The dominant approach to the SLAM problem was introduced in a seminal paper by Smith and Cheeseman in 1986, and first developed into an implemented system by Moutarlier and Chatila [25]. This approach uses the Extended Kalman Filter (EKF) to estimate the posterior over robot pose and maps. There have been several implementations of the EKF-SLAM in different environments, such as indoors [5], underwater [6] and outdoors [7]. The EKF approximates the SLAM posterior as a high-dimensional Gaussian over all features in the map and the robot pose. The single hypothesis data association and quadratic complexity due to the high dimensional Gaussian approximations for states of the robot and landmarks locations, makes the off-diagonal elements of the covariance matrix very large. This causes more complexity and cost increase of computation and, in most cases, diverges the filter [8].In addition, the EKF covariance matrices are quadratic in the size of the map, and updating them requires time quadratic in the number of landmarks [9][10][11][12]. Moreover, when a large number of landmarks are present in the environment, the computation becomes almost impossible. There is another type of filter started to rise and take place in estimation utilizing the principles of the Unscented Kalman Filter (UKF) uses a unique representation of a Gaussian random variable in N dimensions using 2N+1

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.10.585

samples, called sigma points. The representation utilizes the properties of the matrix square root and the covariance definitions to select these points in such a way that they have the same covariance as the Gaussian they approximate [21]. The UKF yields results comparable to a third-order Taylor series expansion of the sate-model, while Extended Kalman Filters are only accurate to a first-order linearization. The Unscented transform approach also has another advantage: noise can be treated in a nonlinear fashion to account for non-Gaussian or non-additive noises. The UKF suffers less from linearization, though it is not exempt. Finally, the UKF does not fully recover from poor landmarks, just as with the EKF.

There is another algorithm which uses the multi hypothesis data association and logarithmic complexity instead of quadratic. This approach, known as Fast-SLAM utilizes Rao-Black wellised particle filter to solve the SLAM problem efficiently. Using Fast-SLAM algorithm, the posterior estimation will be over the robot's pose and landmarks locations. The Fast-SLAM algorithm has been implemented successfully over thousands of landmarks and compare to EKF-SLAM that can only handle a few hundreds of landmarks, it has appeared with considerable advantages [13-16]. As an alternative approach, there is another novel algorithm, known as the smooth variable structure filter (SVSF). The SVSF is a relatively new predictor-correct estimation method based on sliding mode theory [16]. In 2007, the smooth variable structure filter (SVSF) was introduced and is based on variable structure theory and sliding mode concepts [22]. It implements a switching gain to converge the estimates to within a boundary of the true states, referred to as the existence subspace. As demonstrated in the literature, the SVSF provides a robust and stable estimate to modeling uncertainties and errors [20]. This is particularly advantageous when the system model is not well-defined or known to the user.

The development of a new predictor-corrector filter based on sliding mode theory is proposed for state and parameter estimation known as the Smooth Variable Structure Filter (SVSF) which is robust and stable to modeling uncertainties making it suitable for Unmanned Ground Vehicle (UGV) localization and mapping problem. Moreover, the SVSF is a robust recursive predictor-corrector estimation method that can effectively deal with uncertainties associated with initial conditions and modeling errors of Odometer/Laser system. In parameter estimation, the EKF-SLAM strategy is very sensitive to modeling uncertainties and is susceptible to instability. The concept of SVSF-SLAM is reviewed, this new strategy retains the near optimal performance of the SVSF when applied to an uncertain system, it has the added benefit of presenting a considerable improvement in the robustness of the estimation process.

The paper is organized as follows. Section 2 depicts the process model of UGV. Section 3, presents the observation model. Section 4 describes the EKF-SLAM algorithm. Section 5 describes also the SVSF-SLAM algorithm in detail. Section 6 proposes our version of the algorithm SVSF-SLAM. Finally, results in simulation, experiments and conclusion are provided in Section 7 and Section 8 respectively.

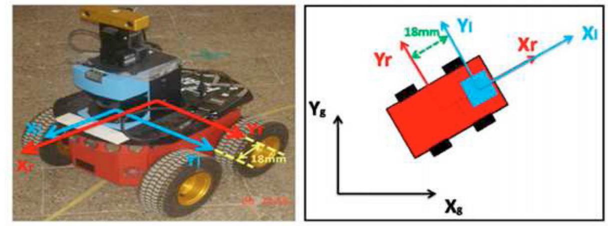

Fig. 1. Representation the UGV (Pioneer 3-AT) equipped with a SICK 2D laser range finder (LMS-200) for 2D mapping.

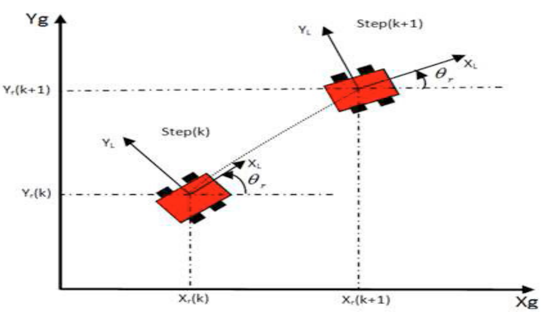

Fig. 2. UGV modeling and representation in the global coordinate system.

2. PROCESS MODEL OF UGV

The Pioneer 3-AT robot figure (1) used in this work is a non-holonymic robot with four wheels. Let the vector $[X_r \quad Y_r \quad \theta_r]$ with $(X_r \quad Y_r)$ the coordinates of the robot in the global coordinate and θ_r it's orientation. The non-holonomic constraint is written as follows [15]:

$$X_r \dot{X}_r sin(\theta_r) - Y_r \dot{Y}_r cos(\theta_r) = 0 \tag{1}$$

From the figure (2), the state transition equation of robot is:

$$\begin{cases} \dot{X}_r = v_x cos(\theta_r) - v_y sin(\theta_r) \\ \dot{Y}_r = v_y sin(\theta_r) + v_y cos(\theta_r) \\ \dot{\theta}_r = w, \end{cases} \tag{2}$$

Mobile robot's motion model and measurement output model are used to describe the motion and the status of robot and landmarks at the next time step, with: w present the rotation speed. When $v_y = 0$, $v = v_x$, and by discretizing expression (2), the model will be written as follows:

$$\begin{pmatrix} X_r(k+1) \\ Y_r(k+1) \\ \theta_r(k+1) \end{pmatrix} = \begin{pmatrix} X_r(k) + \Delta T v_k cos(\theta_r(k)) \\ Y_r(k) + \Delta T v_k sin(\theta_r(k)) \\ \theta_r(k) + \Delta T w(k) \end{pmatrix} + \begin{pmatrix} \varepsilon_{x_r} \\ \varepsilon_{y_r} \\ \varepsilon_{\theta_r} \end{pmatrix}. \tag{3}$$

The robot evolution model reflects the relationship between the robot previous states $X_R(k)$ and its current state $X_R(k+1)$. Let control vector be $U_k = [v, w]^T$, when U_k is put on robot. The robot moves on a plane and receives direction and point landmarks range on the same plane. In SLAM, the system state vector has a position of the UGV (X_R). It is represented by $X_R = [X_r,\ Y_r,\ \theta_r]^T \in \mathbf{R}^3$, and the map is presented by $m_i = [x_1, y_1, ..., x_M, y_M]^T \in \mathbf{R}^{2M}$, with M is the total number of landmarks, ΔT is time step, $\varepsilon_{x_r y_r \theta_r}$ are the noise that arise from the encoder and wheels slipping, etc. We can write equation (3) as follows:

$$X_R(k+1) = f(X_R(k), U(k)) + \varepsilon_{x_r y_r \theta_r}. \tag{4}$$

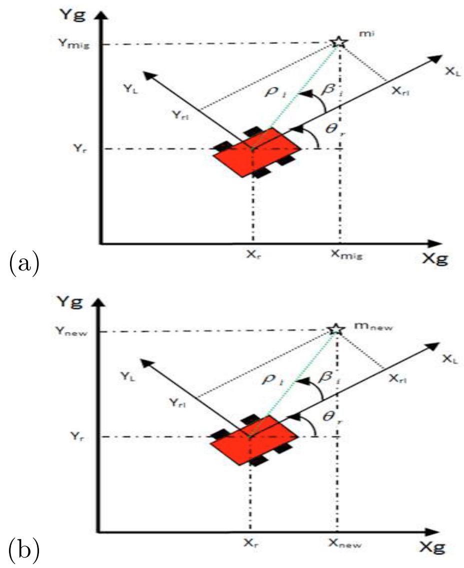

Fig. 3. UGV SLAM: (a) direct observation model and (b) inverse observation model.

3. OBSERVATION MODEL

3.1 Direct observation point based model

Perceptions provide measurements of range and angle of direction of a landmark known position, measured relative to the robot (see figure 3(a)).
We assume that we have m_i numbers of landmark in the environment located at known points. We also assume that the laser range sensor is located vertically above the center of the axe wheels, because this assumption simplifies the equations and study the algorithm. If m_i is known, then the UGV will be used as the location for observation. The observed quantities are nonlinear functions of the state. When at the moment k landmark m_i coordinated $X_{m_{ig}}$ and $Y_{m_{ig}}$ is detected, an angle β_i is measured from the X-axis is the line connecting the center with the landmark benchmark UGV and a range ρ_i between landmark and origin of the coordinate of the UGV connected to the state $[X_r \;\; Y_r \;\; \theta_r]^T$.

The UGV used in our experiment is equipped with a laser range finder (see Figure 1), returning 361 range measurements in a single sweep, with a range resolution of 0.05 m, an angular resolution of 0.5°, a maximum range of 15 $meters(m)$ and a scanning angle of 180°. In the case of the representation of landmark by point, each point of the scan is considered a landmark and is represented by two parameters $[\rho_i, \;\beta_i]$.
The representation of point coordinates in the global frame according to its coordinates in the local frame is given by:

$$\begin{cases} X_{m_{ig}} = X_{rl}cos(\theta_r) - Y_{rl}sin(\theta_r) + X_r, \\ Y_{m_{ig}} = X_{rl}sin(\theta_r) + Y_{rl}cos(\theta_r) + Y_r, \end{cases} \tag{5}$$

The overall transformation to local inverse is given as follows:

$$\begin{cases} X_{rl} = (X_{m_{ig}} - X_r)cos(\theta_r) + (Y_{m_{ig}} - Y_r)sin(\theta_r), \\ Y_{rl} = -(X_{m_{ig}} - X_r)sin(\theta_r) + (Y_{m_{ig}} - Y_r)cos(\theta_r), \end{cases} \tag{6}$$

Where

- $(X_{m_{ig}}; Y_{m_{ig}})$: The coordinates of landmark in the global frame.
- $(X_{rl}; Y_{rl})$: The coordinates of landmark in the local frame.
- (X_r, Y_r) : Position of the robot in the global frame.
- θ_r : The orientation of the robot.

The superscript i is the i^{th} sample in landmark sample sets. The observation is given by $Z(k) = [\rho_i(k), \beta_i(k)]^T$ are the range and bearing of a sensor relative to a landmark. The direct observation models are expressed as:

$$Z_i = \begin{bmatrix} \sqrt{(X_{m_{ig}} - X_r)^2 + (Y_{m_{ig}} - Y_r)^2} \\ tan^{-1}(\dfrac{Y_{m_{ig}} - Y_r}{X_{mr} - X_r}) - \theta_r \end{bmatrix} + \begin{bmatrix} \varepsilon_{\rho_i} \\ \varepsilon_{\beta_i} \end{bmatrix} \tag{7}$$

Where ε_{ρ_i} is the noise of measured range, ε_{β_i} is the bearing in the local frame.

3.2 Inverse observation point based model

Consider the example shown in the figure (3(b)). Where the robot state $(X_r; Y_r)$ and watching a landmark m_{new} with coordinates $(X_{new}; Y_{new})$ using a laser range finder; let $Z_i = [\rho_{il}; \beta_{il}]$ is the observation of landmark m_{new} by the robot.
The landmark mapping model is an inverse observation model, knowing the state of the robot and observation, it can be written as follows:

$$X_{m_i}(k) = h_i^{-1}(X(k), Z_i(k)) \tag{8}$$

$$X_{m_i}(k) = \begin{bmatrix} X_r + \rho_i cos(\theta_r + \beta_i) \\ Y_r + \rho_i sin(\theta_r + \beta_i) \end{bmatrix} \tag{9}$$

4. EKF FILTER

The Kalman Filter (KF), provides an elegant and statistically optimal solution for linear dynamic systems in the presence of Gaussian white noise. It is a method that utilizes measurements linearly related to the states, and error covariance matrices, to generate a gain referred to as the Kalman gain. This gain is applied to the a priori state estimate, thus creating an a posteriori estimate. The following two equations describe the system dynamic model and the measurement model used in general for linear state estimation [16].

$$X_k = F_{k-1}X_{k-1} + W_k \tag{10}$$

$$Z_k = H_k X_k + V_k \tag{11}$$

The next five equations from the KF algorithm, and are used in an iterative fashion, in conjunction with equation (10) and (11). Equation (12) extrapolates the a priori state estimate, and Equation (13) is the corresponding state error covariance. The Kalman gain may be calculated by equation (14), and is used to update the state estimate and error covariance, described by equations (15) and (16), respectively.

$$\hat{X}_{k/k-1} = F_{k-1}\hat{X}_{k-1/k-1} \tag{12}$$

$$P_{k/k-1} = F_{k-1}P_{k-1/k-1}F_{k-1}^T + Q_k \tag{13}$$

$$K_k = P_{k/k-1}H_{k-1}^T[H_k P_{k/k-1} H_k^T + R_k]^{-1} \tag{14}$$

$$\hat{X}_{k/k} = \hat{X}_{k/k-1} + K_k[Z_k - H_k\hat{X}_{k/k-1}] \tag{15}$$

$$P_{k/k} = [I - K_k H_k]P_{k/k-1} \tag{16}$$

The EKF may be used for nonlinear systems. It is conceptually similar to the iterative KF process. The nonlinear system (F) and measurement (H) matrices are linearized according to its corresponding Jacobian, which is a first-order partial derivate. This linearization can sometimes cause instabilities when implementing the EKF [16]. The main steps of the EKF algorithm can be defined as follows (see Figure 4):

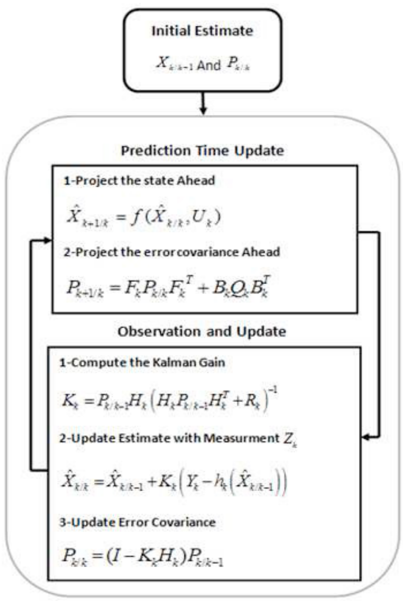

Fig. 4. Algorithm of the EKF FILTER.

We propose an association method that used in the classical EKF-SLAM algorithm "point to point" landmark as shows below in figure 5. The system model and the measurement model in this case are nonlinear. The measurement was left in Cartesian coordinates. In the following

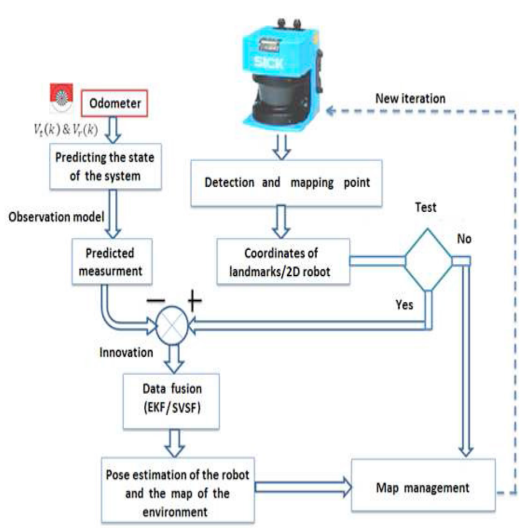

Fig. 5. Steps of the EKF-SLAM principle.

section we investigate the SVSF proposed as an alternative to solve the linearization issue linked to EKF. We begin by considering the form of SVSF to linear systems, before moving on to show the nonlinear SVSF which is necessary to solve our Unmanned Ground Vehicle SLAM problem.

5. SVSF FILTER

In 2007, the smooth variable structure filter (SVSF) was introduced. This filter is based on the sliding mode control and estimation techniques, and is formulated in a predictor-corrector fashion. The SVSF makes use of an existence subspace and of a smoothing boundary layer to keep the estimates bounded within a region of the true state trajectory. This creates a robust and stable estimation strategy. The research presented in this thesis focuses on advancing the development and implementation of the SVSF [17]. As shown in the following figure 5, the SVSF utilizes a switching gain to converge the estimates to within a boundary of the true state values (i.e., existence subspace) [18]. The SVSF has been shown to be stable and robust to modeling uncertainties and noise, when given an upper bound on the level of unmodeled dynamics and noise [18] [19].

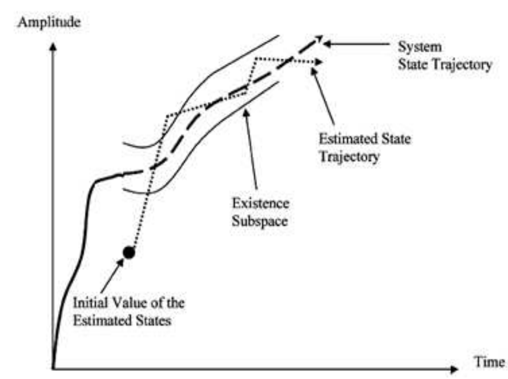

Fig. 6. SVSF Estimation Concept.

The SVSF method is model based and applies to smooth nonlinear dynamic equations. The estimation process may be summarized by equations (17) to (21), and is repeated iteratively. An a priori state estimate is calculated using an estimated model of the system [23][24]. This a priori value is then used to calculate an a priori estimate of the measurement, defined by equation (18). A corrective term, referred to as the SVSF gain, is calculated as a function of the error in the predicted output, as well as a gain matrix and the smoothing boundary layer width. The corrective term calculated in equation (19) is then used in equation (21) to find the a posteriori state estimate. Two critical variables in this process are the a priori and a posteriori output error estimates, defined by equations (22) and (23), respectively [22]. Note that equation (22) is the output error estimate from the previous time step, and is used only in the gain calculation.

$$\hat{X}_{k+1/k} = \hat{f}(\hat{X}_{k/k}, U_k) \tag{17}$$

$$\hat{Z}_{k+1/k} = \hat{h}(\hat{X}_{k+1/k}) \tag{18}$$

U_k is the input control vector. The gain is computed using the a priori and the a posteriori measurement errors, the smoothing boundary layer widths φ , convergence rate γ and measurement matrix H, [22] as follows:

$$K_{k+1}^{SVSF} = \hat{H}|(|e_{z_{k+1/k}}|_{ABS} + \gamma|e_{z_{k/k}}|_{ABS})|Sat(e_{z_{k+1/k}}, \varphi) \tag{19}$$

Where the saturation function is defined by:

$$Sat(e_{z_{i,k+1/k}}, \varphi) = \begin{cases} +1, & \frac{e_{z_{i,k+1/k}}}{\varphi_i} \geq 1 \\ \frac{e_{z_{i,k+1/k}}}{\varphi_i}, & -1 < \frac{e_{z_{i,k+1/k}}}{\varphi_i} < 1 \\ -1, & \frac{e_{z_{i,k+1/k}}}{\varphi_i} \leq -1. \end{cases} \quad (20)$$

The update of the state estimates can be calculated as follows:

$$\hat{X}_{k+1/k+1} = \hat{X}_{k+1/k} + K_{k+1}^{SVSF} e_{z_{k+1/k}} \quad (21)$$

$$e_{z_{k+1/k}} = Z_{k+1} - \hat{Z}_{k+1/k} \quad (22)$$

$$e_{z_{k/k}} = Z_k - \hat{Z}_{k/k} \quad (23)$$

The SVSF filter is stable and robust to modeling uncertainties given an upper bound for uncertainties and noises as well as it can be to linear or nonlinear system [22].

6. SVSF-SLAM

Simultaneous Localization and Mapping (SLAM) is the problem of constructing a model of the environment being traversed with on board sensors, while at the same time maintaining an estimation of the vehicle location within the model [20]. As an alternative approach, there is another novel filter, known as the smooth variable structure filter (SVSF).The SVSF is a relatively new predictor-correct estimation method based on sliding mode theory; this filter provides a robust and stable estimate to modeling uncertainties and errors [21].

In the following section we investigate the SVSF proposed as an alternative to solve the linearization issue linked to EKF. We begin by considering the form of SVSF to linear systems, before moving on to show the nonlinear SVSF which is necessary to solve our Unmanned Ground Vehicle SLAM problem.

The initial conditions used by the SVSF-SLAM were the same as those used by the EKF-SLAM. There are two main SVSF design parameters. The first parameter (γ) which control the speed of convergence, where the second (φ) refers to the boundary layer width which is used to smooth out the switching action. These parameters should be chosen carefully. γ is is a diagonal matrix with elements were set to the following:

$$0 < \gamma_i \leq 1 \quad (24)$$

The SVSF process may be summarized by (17) through (21), and is repeated iteratively. According to [22], the estimation process is stable and converges to the existence subspace if the following condition is satisfied:

$$|e_{k/k}|_{ABS} > |e_{k+1/k+1}|_{ABS} \quad (25)$$

In this section, a framework for feature map SLAM based on the SVSF are presented. Like EKF-SLAM, SVSF-SLAM is a kind of stochastic SLAM algorithm, which is performed by storing the vehicle pose and map features in a single state vector. It consists of following stages: initialization, prediction, data association and update, finally the management of the map.

SVSF-SLAM Algorithm

- **Initial Estimate**

$$\hat{X}(0) = [\hat{X}(0), \hat{m}_1, ..., \hat{m}_M]^T; \quad e_{0/0}^Z = [e_0^{Z,1} ... e_0^{Z,M}]^T \quad (26)$$

- **Prediction Time Update**

The prediction stage is a process, which deals with vehicle motion based on incremental dead reckoning estimates and increases the uncertainty of the vehicle pose estimate. First, the state vector is augmented with a control input $U(k)$. Consider the following process for the SVSF estimation strategy, as applied to a nonlinear system with a linear measurement equation. The predicted state estimates $\hat{X}_{k+1/k}$ are first calculated as follows:

$$\hat{X}_{k+1/k} = f(\hat{X}_{k/k}, \hat{U}(k)) \quad (27)$$

This motion model is generally nonlinear in its arguments.

- **Data association and update**

If a feature already stored in the map is observed by a range bearing sensor with the measurement $Z(k)$ and the observation error covariance is R_k.

The a priori measurement error vector $e_{z_{k+1/k}}$ (dimension: 2x1) may be calculated:

$$e_{z_{k+1/k}} = Z_{k+1} - \hat{Z}_{k+1/k} \quad (28)$$

The a posteriori measurement error vector $e_{z_{k+1/k}}$ (dimension: 2x1) may be calculated:

$$e_{z_{k/k}} = Z_k - \hat{Z}_{k/k} \quad (29)$$

The SVSF gain K_{k+1}^{SVSF} is calculated as follows:

$$K_{k+1}^{SVSF} = \hat{H}|(|e_{z_{k+1/k}}|_{ABS} + \gamma|e_{z_{k/k}}|_{ABS})|Sat(e_{z_{k+1/k}}, \varphi) \quad (30)$$

The gain vector K_{k+1}^{SVSF} is used to formulate an a posteriori state estimate and the update of the state estimates can be calculated as follows:

$$\hat{X}_{k+1/k+1} = \hat{X}_{k+1/k} + K_{k+1}^{SVSF} e_{z_{k+1/k}} \quad (31)$$

$$\hat{X}_{k+1/k} = h(\hat{X}_{k+1/k}) \quad (32)$$

Note that the matrix $\Delta h = \frac{\partial h(X_{k+1/k})}{X_R(k+1)}$ is a Jacobian matrix with partial derivatives of the system $h(X)$.

$$\Delta h_k = [H_{R,k} \quad 0 \quad ... \quad H_{m_i,k} \quad ...0] \quad (33)$$

Such that:

$$H_{R,k} = \frac{\partial h(X_{k+1/k})}{\partial X_R}$$

and

$$H_{m_i,k} = \frac{\partial h(X_{k+1/k})}{\partial X_{m_i}}$$

The SVSF gain is a feature of the a priori and a posteriori measurement error vectors $e_{z_{k+1/k}}$ and $e_{z_{k/k}}$ the smoothing boundary layer widths φ_i.

The estimation equation of SVSF-SLAM is computationally simpler than EKF-SLAM and the updating form of SVSF is more suitable than EKF. The SVSF-SLAM performed significantly better than the EKF-SLAM, in terms of estimation error. In order to be processed by SVSF algorithm as shows in figure (7), each measurement extracted from the sensor data must be associated to the corresponding either line or point present in the map. Only the matching features can be used to update the robot pose and the map.

- **Management of the map**

As the environment is explored, new features are observed and should be added to the stored map. In this case, the state vector and the output error estimate matrix are calculated of the new observation. This research focused on advancing the development and implementation of the SVSF-SLAM. To reiterate, the SVSF was introduced in 2007, and is based on variable structure theory and sliding mode concepts. It implements a switching gain to converge the estimates to within a boundary of the true states, referred to as the existence subspace. As demonstrated in literature, and reinforced throughout this paper, the SVSF-SLAM provides a robust and stable estimate to modeling uncertainties and errors.

· Initial a new Landmark a_{new}

$$a_{new} = h^{-1}(\hat{X}_{k+1/k+1}, Z_{k+1/k}) \tag{34}$$

· Initial a posteriori state estimate of new landmark

$$e_{Z,new} = Z_{k+1} - h(\hat{X}_{k+1/k+1}, a_{new}) \tag{35}$$

· Incremented of the state vector $\hat{X}_{Incremented}$

$$\hat{X}_{Incremented} = [\hat{X}_{k+1}; a_{new}] \tag{36}$$

After navigating in unknown environment, detect that the robot has returned to a previous position has a big benefit in order to increase the accuracy and consistency of the estimation. Furthermore, detecting closure of the loop is essential for improving the robustness of the SLAM algorithm.

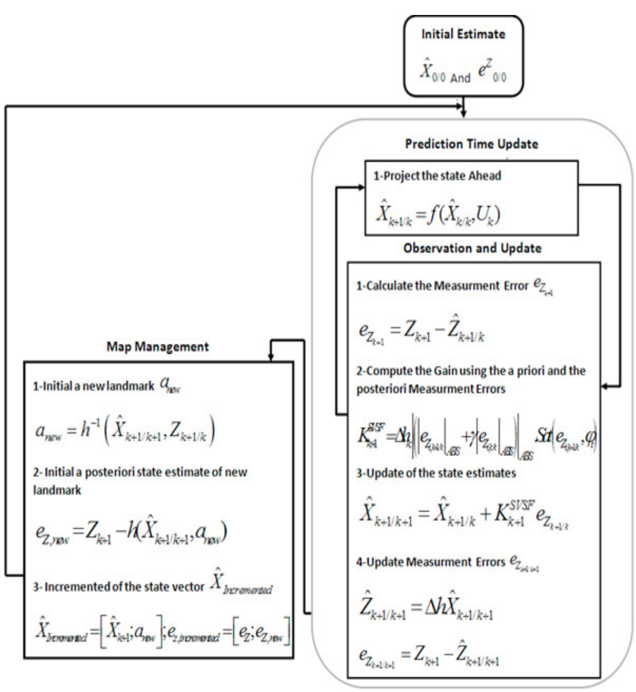

Fig. 7. Algorithm of the SVSF-SLAM.

7. SIMULATION, EXPERIMENTS AND DISCUSSION

We present our simulation results to validate the proposed SVSF-SLAM for Unmanned Ground Vehicle localization problem. The results of our approach are compared with EKF-SLAM navigation filtering. The sampling rates used for each filter and sensors used in this study are as follows: $f_{odometer} = f_{laser} = f_{EKF-SLAM} = f_{SVSF-SLAM} = 10Hz$

First, the simulation results provided in the following figures represent the estimated UGV position obtained using the EKF, and SVSF filters respectively with $\sigma_x = \sigma_y = 10^{-4}m$, $\sigma_\theta = 10^{-4}rad$ and $\gamma = diag(0.8 \quad 0.8)$, $\varphi = diag(10, 12)$.

First experiment: with white centred Gaussian noise: In the first experiment we assume a white centred Gaussian noise, for process and observation model where: $\sigma_v = 0.1m/s$, $\sigma_w = 0.25rad/s$, $\sigma_\rho = 0.1m$, $\sigma_\beta = 0.25rad$.

$$Q_k = \begin{bmatrix} (0.1)^2 & 0 \\ 0 & (0.25)^2 \end{bmatrix}, \; R_k = \begin{bmatrix} (0.1)^2 & 0 \\ 0 & (0.25)^2 \end{bmatrix}$$

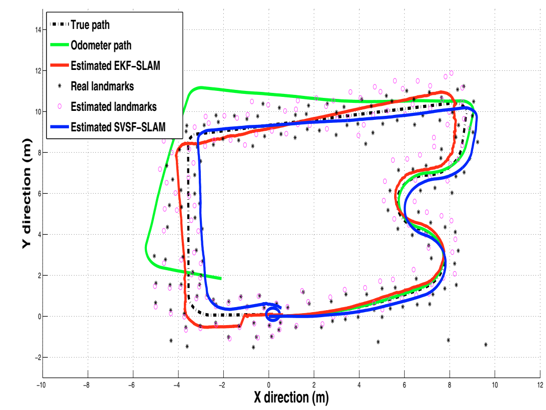

Fig. 8. Robot pose estimation using EKF/SVSF-SLAM with white centred Gaussian Noise.

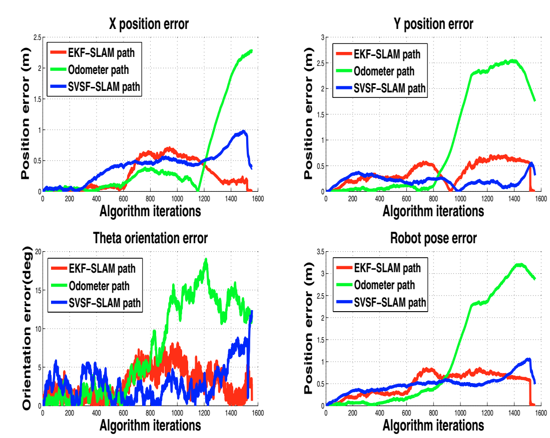

Fig. 9. Position error of SLAM by both approaches with white centred Gaussian Noise.

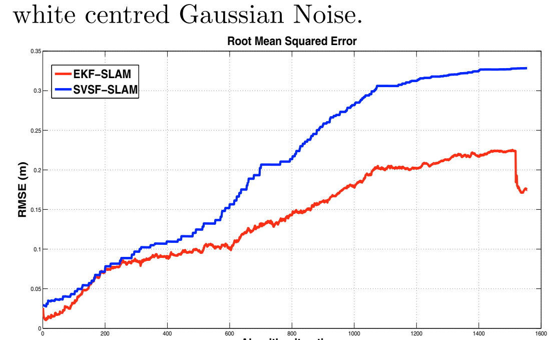

Fig. 10. RMSE for the EKF-SLAM and SVSF-SLAM algorithms with white centred Gaussian Noise.

Second experiment: with non centred Gaussian noise: In this experiment we assume a white noise with bias, for process and observation model where: $\sigma_v = 0.1m/s$, $\sigma_w = 0.08rad/s$, $\sigma_\rho = 0.045m$, $\sigma_\beta = 0.045rad$.

$$Q_k = \begin{bmatrix} (0.1)^2 & (0.045)^2 \\ (0.045)^2 & (0.08)^2 \end{bmatrix}, \; R_k = \begin{bmatrix} (0.045)^2 & (0.03)^2 \\ (0.03)^2 & (0.045)^2 \end{bmatrix}$$

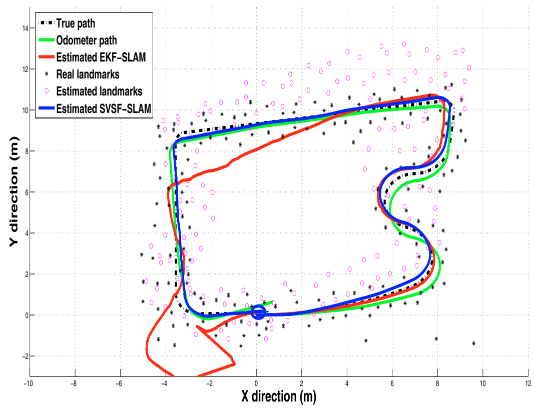

Fig. 11. Robot pose estimation using EKF/SVSF-SLAM with non centred Gaussian noise.

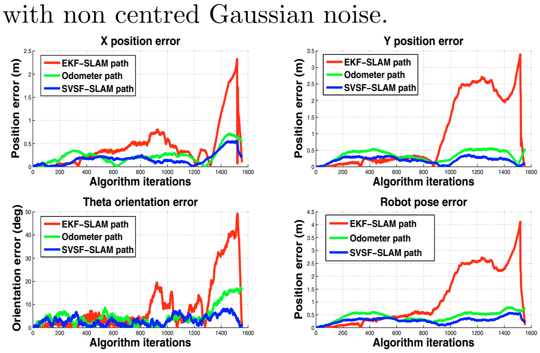

Fig. 12. Position error of SLAM by both approaches with non centred Gaussian noise.

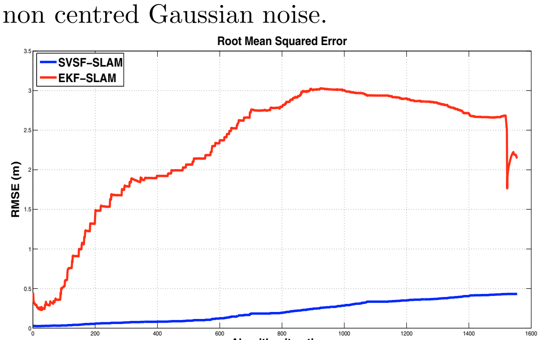

Fig. 13. RMSE for the EKF-SLAM and SVSF-SLAM algorithms with non centred Gaussian noise.

Third experiment: with colored noise: In this experiment and in order to see the robustness of the SVSF-SLAM algorithm, we assume a colored noise, for process and observation model where: $\sigma_v = 0.2m/s$, $\sigma_w = 0.15rad/s$, $\sigma_\rho = 0.02m$, $\sigma_\beta = 0.02rad$.

$$Q_k = \begin{bmatrix} (0.2)^2 & (0.1)^2 \\ (0.1)^2 & (0.15)^2 \end{bmatrix}, \; R_k = \begin{bmatrix} (0.02)^2 & (0.03)^2 \\ (0.03)^2 & (0.02)^2 \end{bmatrix}$$

Figure 8, 11 and 14 present the results of comparison

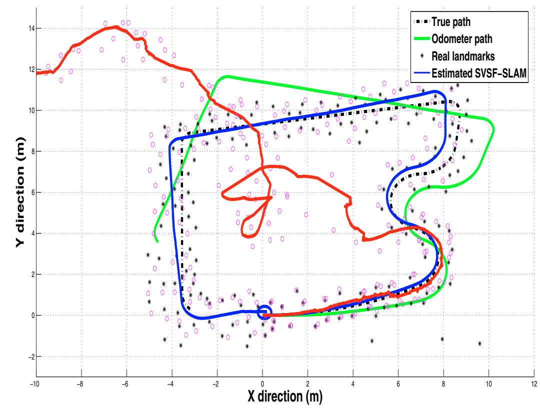

Fig. 14. Robot pose estimation using EKF/SVSF-SLAM with colored Noise.

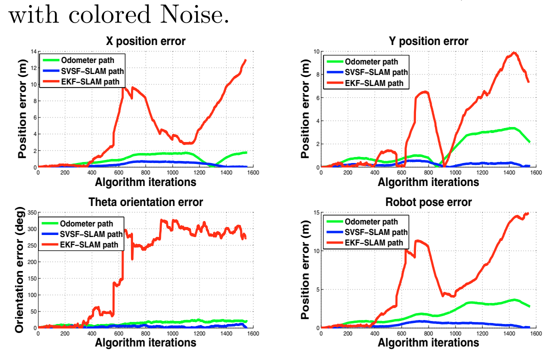

Fig. 15. Position error of SLAM by both approaches with colored noise.

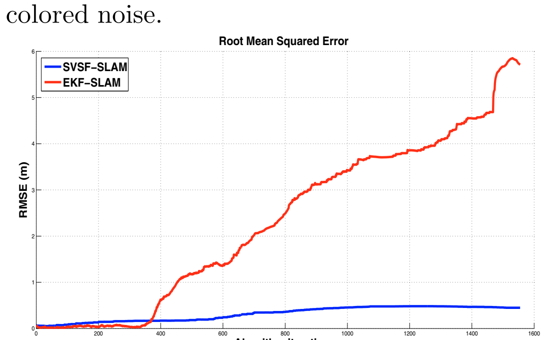

Fig. 16. RMSE for the EKF-SLAM and SVSF-SLAM algorithms with colored noise.

of the estimated position of the UGV given by the EKF-SLAM and SVSF-SLAM. As can be seen from these figures when the process and observation noises are centred white Gaussian noises the EKF-SLAM performs much better than the SVSF-SLAM (accurate position with accurate map, Figure 8). In Figures 11 and 14, when the noise is note centred or not white, we can observe that the SVSF-SLAM performs much better than the EKF-SLAM which confirms the robustness of the proposed approach.

The UGV poses errors when the noise is: zero mean white, white with bias and colored are shown in figures 9, 12 and 15 respectively. These figures confirm the previous conclusion, and it is clear that the SVSF-SLAM maintains a suitable accuracy of the UGV pose when the noise characteristics are unknown (without any assumption). The SVSF was able to overcome the lack of information after a few time steps, and provide a relatively good estimate. In the other hand, the EKF-SLAM requires zero mean white noise, otherwise the errors pose increase significantly following x, y and θ (Figures 12 and 15). Moreover, from the same figures we can observe that at the iteration 1550 a loop closing is detected (the UGV observes features already observed previously). At this moment we observe a significant improvement of the accuracy of the EKF-SLAM as well the SVSF-SLAM especially in the two first experiments. When the robot closes the loop (revisiting old landmarks), SLAM algorithm will also correct the positions of landmarks (the map).

Finally, the RMSE (Root Mean Square Error) for the UGV position in the three experiments is given in Figures (10, 13 and 16) respectively. In the first experiment comparing the RMSE of SVSF-SLAM and EKF-SLAM, in the presence of white Gaussian noise, we observe that the EKF-SLAM give the best result, in this case, with zero mean white Gaussian noise, as can be seen from Figure 9, EKF-SLAM algorithm gives the best results position and is more accurate than SVSF-SLAM algorithm. This can interpreted by the optimality of the EKF when the process and observation models are accurately known, also, when the process and observation noises are uncorrelated zero mean Gaussian with known covariance. However the SVSF-SLAM provides the best RMSE than the EKF-SLAM, when we use non centred Gaussian noise as shown in the figures 13 and 16. These results clearly validate the advantage of the SVSF-SLAM over the EKF-SLAM especially when the system or observation models are not accurate enough and the process and observation noises are non centered Gaussian noise. This result is confirmed by the third experiment, when the process and observation model are not white. Furthermore, when a loop closure is detected significant decrease of the RMSE is obtained for both algorithms. Figure 17 shows the comparison of the computational time between the two algorithms of SLAM. As can be seen from this figure, we see clearly that the computational time of the SVSF-SLAM is much better than the EKF-SLAM. The computational time of this latter is increasing with the size of the state vector which increases when new features are observed, because the full state vector is used for prediction and update. In the other hand, the SVSF-SLAM algorithm updates only the UGV pose and the associated features, which makes it faster than the EKF-SLAM.

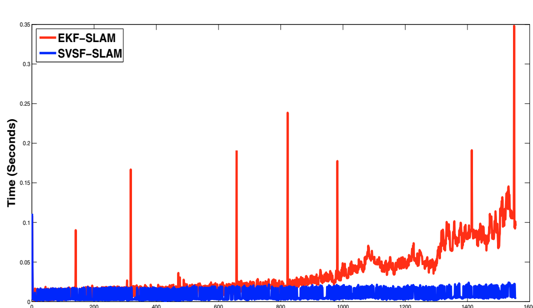

Fig. 17. Computational time of SLAM by both approaches
.

8. CONCLUSION

In this paper the SVSF-SLAM algorithm is implemented using odometer and LASER data to construct a map of the environment and localize the UGV within this map. The proposed algorithm is validated and compared to the EKF-SLAM algorithm. Good results are obtained by the SVSF-SLAM comparing to the EKF-SLAM, especially when the noise is colored or affected by a variable bias. Which confirm the efficiency of our approaches. The proposed SVSF-SLAM algorithm provides a slightly accurate position than EKF. Performances improvement of the SVSF-SLAM comparing to the EKF-SLAM can appear clearly when the process and measurement noises are non centered or modeling errors are unknown. Under these assumptions the EKF-SLAM provides poor performances. However, due to the corrective action of the SVSF-SLAM gain its corresponding estimate remains bounded within a region of the true state estimate. The obtained results confirm the robustness of the proposed approach for UGV localization and mapping.

REFERENCES

Golombek M. P.,Cook R. A.,Economou T.,Folkner W.M., Haldemann A. F. and al. (1997). Overview of the mars pathfinder mission and assessment of landing site predictions. *Science*, 278, no.5344 , 1743-1748, December.

Thrun S., Ferguson D., Haehnel D., Montemerlo M., Burgard W., and Triebel R. (2003). A system for volumetric robotic mapping of abandoned mines. *In proceedings of the IEEE International Conference on Robotics and Automation (ICRA'03).*

Leonard J., Tardòs J.D. , Thrun S. , and Choset H. (2002). Eds. Workshop Notes of the ICRA Workshop on Concurrent Mapping and Localization for Autonomous Mobile Robots (W4). *ICRA Conference, Washington, DC.*

Thorpe C. and Durrant-Whyte H. (2001). Field robots. *ISRR.*

Leonard J.J., Newman P.M., Rikoski R.J. , Neira J. and Tardòs J.D.. Towards Robust Data Association and Feature Modelling for Concurrent Mapping and Local ization. *ISRR-01.*

Williams SB, Dissanayake G . and Durrant-Whyte H. (2001). Constrained Initialisation of the Simultaneous Localization and Mapping Algorithm. *3rd International Conference on Field and Service Robotics.* Service Robotics (FSR) June 10-13, Espoo, Finland, 315-320.

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

Andrew Davison J. , Reid Ian D., Molton Nicholas D. , and Stasse O. (2007). MonoSLAM: Real-Time Single camera SLAM. *In Conference on Pattern Analysis and Machine Intelligence*, 29.

Hugh Durrant-Whyte and Time Bailey (2006). Simultane ous Localisation ans Mapping: Part I. *Robotics & Au tomation Magazine*, 13, 99-110, June.

Jensfelt P., Kragic D., Folkesson J. , and Bjorkman M. (2006). A framework for vision based bearing only

3D SLAM. *In International Conference on Robotics and Automation*, 1564-1570.
Andrew J. Davison (2003). Real-Time Silultaneous Localisation and Mapping with a single Camera. *In Ninth IEEE International Conference on Computer Vision*, Nice, France, 1403-1410.
Michael Montemerlo, Sebastian Thrun, Daphne Koller, and Ben Wegbreit (2003). FastSLAM 2.0 an improved Particle Filtering Algorithm for Simultaneous Localization and Mapping that provably Converges. *In proceedings of the Sixteenth International Joint Conference on Artificial Intelligence*, Acapulco.
Al-Shabi M. (2011). The General Toeplitz/Observability SVSF. *Department of Mechanical Engineering*, McMas ter University, Hamilton, Ontario, Ph.D. Thesis.
Montemerlo M., Thrun S., Koller D. , and Wegbreit B. (2002). FastSlam: A Factored Solution to the Simultaneous Localization and Mapping Problem. *AAAI*.
Doucet A. , Freitas J.F.G., and Gordon N.J. (2001). Sequential Monte Carlo Methods In Practice. *Springer*.
Doucet A., Freitas N., Murphy K., and Russell S. (2000). Raoblackwellised particle filtering for dynamic bayesian networks. *UAI*.
Davision A. J. and Kita N. (2001). 3D Simultaneous Localisation and Map-Building Using active Vision for Robot moving on Undulating Terrain. *In Computer Vision and Pattern Recognition*.
Lemaire T., Lacroix S., and Sola J. (2005). A pratical 3D Bearing-Only SLAM algorithm. *In International Conference on Intelligent Robots and Systems*, 2449-2454.
Andrew J. Davison, Yolanda Gonzalez Cid, and Nobuyuki Kita (2004). Real-Time 3D SLAM with Wide-Angle Vision. *In proceedings of the IFAC Symposium on Intelligent Autonomous Vehicules*, Lisbon.
Habibi S. R. and Burton R. (2003). The Variable Structure Filter. *Journal of Dynamic Systems, Measurement, and Control (ASME)*, 125,287-293, September.
Fredrik Orderud (2005). Comparison of Kalman Filter estimation approaches for state space models with Nonlinear measurements. *In Scandinavian Conference on Simulation and Modeling*.
Miguel Angel Garcia and Agusti Solanas (2007). 3D Simultaneous Localisation and Modeling from Stereo Vision.*In International Conference on Robotics and Automation*, New Orleans, 847-853.
Habibi S. R. (2007). The Smooth Variable Structure Filter. *Proceedings of the IEEE*, 95, no. 5, 1026-1059.
Gadsden S. A., Dunne D., Habibi S. R. and Kirubara jan T.(2013). Comparison of Extended and Unscented Kalman, Particle, and Smooth Variable Structure Filters on a bearing-Only Target Tracking Problem. *Proc. Of SPIE* , 7445, 74450B-1.
Moutarlier P. and Chatilla R. (1989). Stochastic multisensory data fusion for mobile robot location and environment modeling,in International Symposium of Robotics Research.