Improved Unscented FastSLAM Using Geometric Information of Particles

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***Abstract*—This paper presents an improved unscented fast simultaneous localization and mapping (UFastSLAM) using the geometric information of particles. The information are the pose of particles and their geometric relation, which are utilized in both the importance weight and the resampling steps. In the importance weight step, all particles are grouped via their weights and updated more accurately using the weight compensation scheme. In addition, the particle depletion problem is overcome by the particle formation technique using geometric relation between particles. The superior performance of the proposed approach over UFastSLAM is validated by the well-known Victoria Park dataset.**

***Index Terms*—rao - blackwellized particle filter, UFastSLAM, EM algorithm, triangular mesh generation**

I. Introduction

Map building and self-localization are fundamental cognitive capacities required for intelligent robots to realize true autonomy. Simultaneous Localization and Mapping (SLAM) is an important technique for such robots, as it addresses the problem of incrementally building an environment map using only onboard sensors carried by a robot and of localizing the robot itself using the built map without relying on any external reference systems, e.g., GPS or Intelligent System.

For SLAM, one of fundamental techniques is FastSLAM which uses the particle filter for the robot pose estimation, and EKF for the feature estimation. There have been many investigations on FastSLAM [1]. However, FastSLAM suffers from some drawbacks, namely, the problem caused by the derivation of the Jacobian matrices and the linear approximations of the nonlinear functions [2]. To solve these problems, many researchers have proposed UFastSLAM [2]-[5]. UFastSLAM overcomes the problems caused by linearization in the FastSLAM framework.

In [2], a full version of the UFastSLAM algorithm is presented. In this approach, Unscented Kalman Filter (UKF) is used to update the mean and covariance of the feature and to initialize new features. Also, UT is used in the prediction step of the vehicle state, and the unscented particle filter provides a better proposal distribution without the accumulation of linearization errors [6] and without the need to calculate the Jacobian matrices in the measurement updates.

In our previous work [7], FastSLAM is improved by considering geometric relation between particles in both the important weight step and the resampling step. To enhance the weight of each particle, two groups are generated according to the compensation scheme. In addition, triangular formation structure are generated during the resampling step which removes the particle depletion problem.

In this paper, we enhance UFastSLAM instead of FastSLAM by adopting the compensation scheme and the formation structure. In Section 2, UFastSLAM is introduced and the problems are described. Section 3 represents the proposed approach in detail. Also, to verify the validity of the proposed approach, a test using the Victoria Park dataset is performed in Section 4. Section 5 concludes this paper by summarizing whole sections.

II. Problem Description

In this paper, we consider the Unscented FastSLAM (UFastSLAM), which is a robust and efficient solution to the SLAM problem. Like FastSLAM, it also shows a factored representation of the SLAM posterior over robot poses and maps, as follows:

$$\begin{aligned} p(x_{1:t}, M \mid z_{1:t}, u_{1:t}, c_{1:t}) &= p(x_{1:t} \mid z_{1:t}, u_{1:t}, c_{1:t})\, p(M \mid x_{1:t}, z_{1:t}, u_{1:t}, c_{1:t}) \\ &= \underbrace{p(x_{1:t} \mid z_{1:t}, u_{1:t}, c_{1:t})}_{\text{path posterior}} \underbrace{\prod_{n=1}^{N_f} p(m_n \mid x_{1:t}, z_{1:t}, u_{1:t}, c_{1:t})}_{\text{landmark estimators}}. \end{aligned} \tag{1}$$

here $x_{1:t}$, $z_{1:t}$ and $u_{1:t}$ are the robot pose, sensor observation and control input up to time t, respectively. Also, $c_{1:t}$ denotes the set of data associations until time t, in which each c_t specifies the identity of the landmark observed at time t. M denotes the entire map consisting of N_f observed features. m_n denotes the nth landmark. The factored representation means that if a path of the robot is given, each landmark can be independently estimated by its own UKF.

To consider the robot pose and the map, the ith particle is denoted by

$$X_t^{[i]} = \left\langle x_t^{[i]}, \mu_{1,t}^{[i]}, \Sigma_{1,t}^{[i]}, \ldots, \mu_{N_f,t}^{[i]}, \Sigma_{N_f,t}^{[i]} \right\rangle \tag{2}$$

where $[i]$ indicates the index of the particle, $x_t^{[i]}$ is the ith particle's pose, and $\mu_{N,t}^{[m]}$ and $\Sigma_{N,t}^{[m]}$ are the mean and the covariance of the Gaussian distribution representing the

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N_fth feature location that are conditioned on the robot path $x_t^{[i]}$.

In UFastSLAM, the robot pose is sampled and the features are estimated using UKF. The importance weight $w_t^{[m]}$ is assigned to the mth particle as follows.

$$w_t^{[m]} = \left|2\pi L_t^{[m]}\right|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z-\hat{z}_t^{[m]})^T \left(L_t^{[m]}\right)^{-1}(z-\hat{z}_t^{[m]})\right\} \quad (3)$$

$$L_t^{[m]} = \left(\Sigma_t^{x,n[m]}\right)^T \left(P_t^{[m]}\right)^{-1} \Sigma_t^{x,n[m]} + \bar{S}_t^{[m]} \quad (4)$$

where $\Sigma_t^{x,n[m]}$, $P_t^{[m]}$ and $\bar{S}_t^{[m]}$ are the cross-covariance, the covariance and the innovation covariance of the mth particle, respectively. In addition, $z-\hat{z}_t^{[m]}$ is the innovation vector.

In the resampling step, the death or life of particles is up to the score of the importance weight. Some particles with relatively large mismatches with their target, called bad particles, are rejected. Another particles with relatively small mismatches with the target, called good particles, are replicated according to the resampling scheme.

However, UFastSLAM has been suffering from the particle depletion problem and the filter convergence problem which are caused by the improper weights and the brutal rejection and replication during the resampling phase.

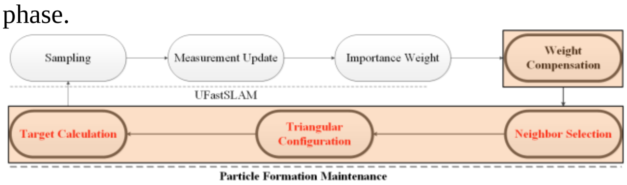


Figure 1. Block diagram for the improved UFastSLAM using geometric information. Four steps for weight compensation and particle formation maintenance are added to UFastSLAM.

III. Proposed Approach

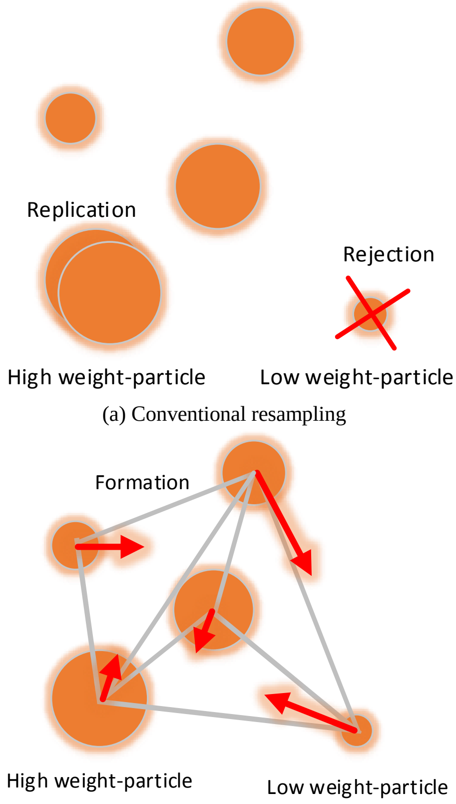
The geometric information of particles are used to overcome the above mentioned problems by compensating the weight of each particle and constituting a formation among particles as shown in Fig. 1.

A. Weight Compensation

For the compensation of the weight, we used an effective clustering technique that are the EM algorithm and k-means algorithm. To compensate the weight of the mth particle $w_t^{[m]}$, the scheme is represented as follows:

$$wc_t^{[m]} = \begin{cases} 0 & \text{,where } X_t^{[m]} \notin S_{h\text{var}} \text{ and } X_t^{[m]} \notin S_{l\text{var}} \\ (1-\frac{1}{\alpha})w_t^{[m]} + \frac{\beta}{\alpha} w_t^{[m\_near]} & \text{,where } X_t^{[m]} \in S_{l\text{var}} \text{ or } X_t^{[m]} \in S_{h\text{var}} \\ \frac{\gamma-1}{\gamma} w_t^{[m]} & \text{, where } X_t^{[m\_near]} \text{ not exist} \end{cases} \quad (5)$$

where $wc_t^{[m]}$ is the compensated weight of the mth particle. S_{hvar} and S_{lvar} denote the set of particles of which weights are to be increased and the set of particles of which weights are to be decreased, respectively. [m_near] means the geometrically nearest particle to the mth particle. α, β and γ are empirically defined.



(b) Proposed resampling

Figure 2. Comparison between the conventional resampling scheme and the proposed resampling scheme. Unlike the conventional resampling scheme, particles are aligned with respect to the proposed resampling scheme without the particle rejection and replication.

B. Particle Formation Maintenance

The resampling part can be replaced with a formation structure specifically that is generated by the triangular form as shown in Fig. 2. To form the triangular structure, particles are selected one by one according to the order of the N-dimension distance array. It is obtained by the distance between the mth particle and the center of the particles that is given by

$$dist^{[m]} = \sqrt{\left(\frac{1}{N}\sum_i x_{x,t}^{[i]} - x_{x,t}^{[m]}\right)^2 + \left(\frac{1}{N}\sum_i x_{y,t}^{[i]} - x_{y,t}^{[m]}\right)^2} \quad (6)$$

If a particle is selected from the above process, a target pose of the particle $\{x\_\text{target}_{x,t}^{[m]}, x\_\text{target}_{y,t}^{[m]}\}$ is computed by

$$x\_\text{target}_{x,t}^{[m]} = x_{ct.x} + k_{T_m} d_m \cos(\phi + \pi/2)\big/\sqrt{3} \quad (7)$$

$$x\_\text{target}_{y,t}^{[m]} = x_{ct.y} + k_{T_m} d_m \sin(\phi + \pi/2)\big/\sqrt{3} \quad (8)$$

where $x_{ct.x}$ and $x_{ct.y}$ are the x-y pose for the center of gravity of triangular configuration T_m which consists of $x_t^{[n_1]}$, $x_t^{[n_2]}$ and $x_t^{[m]}$. $x_t^{[n_1]}$ and $x_t^{[n_2]}$ are the nearest neighbors of $x_t^{[m]}$. ϕ represents the angle which is perpendicular to the line passing through $x_t^{[n_1]}$ and $x_t^{[n_2]}$. k_{T_m} is the average weight factor of T_m. d_m is a scaling factor and defined as $dist^{[m]}$.

The angle of the target, $x\_\mathrm{target}_{\theta,t}^{[m]}$, is determined by the average of three angles in T_m.

From the target pose, the final pose of the mth particle, $x_t^{[m]} = \left\{x_{x,t}^{[m]}, x_{y,t}^{[m]}, x_{\theta,t}^{[m]}\right\}$, is given by

$$x_{x,t}^{[m]} = x_{x,t}^{[m]} + k^{[m]}\left(x\_\mathrm{target}_{x,t}^{[m]} - x_{x,t}^{[m]}\right) \tag{9}$$

$$x_{y,t}^{[m]} = x_{y,t}^{[m]} + k^{[m]}\left(x\_\mathrm{target}_{y,t}^{[m]} - x_{y,t}^{[m]}\right) \tag{10}$$

$$x_{\theta,t}^{[m]} = x_{\theta,t}^{[m]} + k^{[m]}\left(x\_\mathrm{target}_{\theta,t}^{[m]} - x_{\theta,t}^{[m]}\right) \tag{11}$$

where $k^{[m]}$ is the weight factor of the mth particle that is computed by

$$k^{[m]} = \left(1 - \frac{wc_t^{[m]}}{\sum_i wc_t^{[i]}}\right) \tag{12}$$

The weight factor ranges from 0 to 1. If $k^{[m]}$ is equal to 0, the particle has been stopped at its current pose. Otherwise, the particle approaches to the target pose. Since $k^{[m]}$ is proportional to the uncertainty of the mth particle, large uncertainty in the pose of the particle can be compensated after the particle formation maintenance.

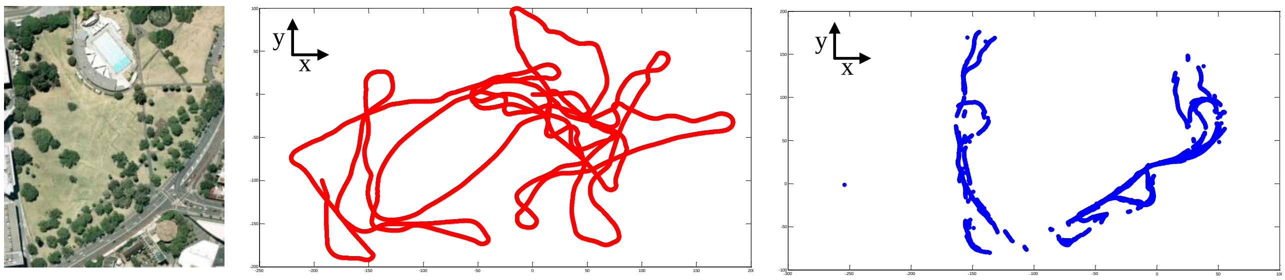
The above mentioned whole process is iteratively operated until all particles are moved.

IV. Experiment

To verify the SLAM performance of the proposed approach, we use a formal dataset that is Victoria Park dataset. In addition, the performance of the proposed approach and UFastSLAM are compared in terms of accuracy of state estimations for localization of a robot and mapping of its environment using GPS data.

A. *Victoria Park Dataset*

The proposed approach is verified using Victoria Park dataset, which is well-known dataset described in [8]. This dataset has 6898 odometry time steps, and it offers logged range/bearing measurements from a laser range sensor. Trees in a park are used as natural features, and they are detected by a tree detection algorithm. The test was conducted on Intel® Core™ i5-2500 CPU 3.30-GHz. Fig. 3(a) shows Victoria Park in Australia provided by Google Maps. Also, Fig. 3(b) and Fig. 3(c) represent the raw odometry trajectory and trajectory obtained from GPS, respectively. From the two trajectories, we can easily know that the odometry data are highly corrupted by noise.

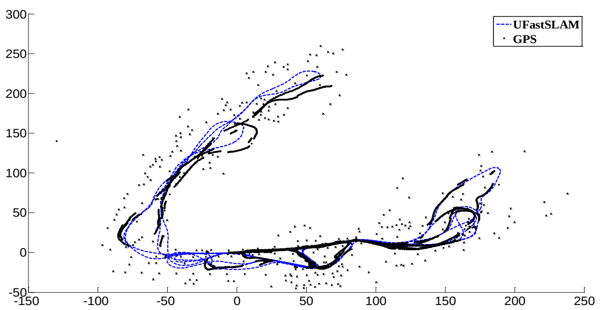


(a) (b) (c)

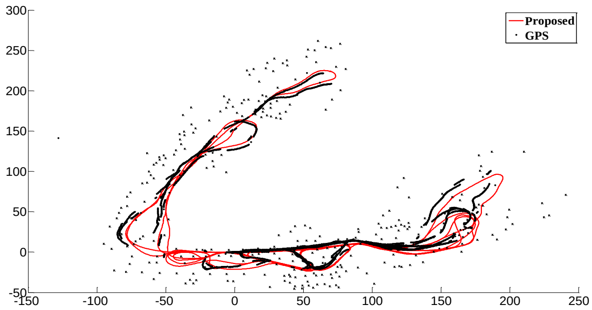
Figure 3. Victoria Park dataset. (a) shows Victoria Park on Google Maps. (b) and (c) represent robot trajectories obtained from odometry and GPS, respectively.

B. *Performance Comparison*

For the performance comparison, GPS data was used as the reference data because GPS data followed true robot trajectory accurately. In addition, only three particles were employed to estimate the robot pose and the map, which is the minimum number of particles to form the triangular structure.



(a) UFastSLAM



(b) Proposed approach

Figure 4. SLAM test using the Victoria Park dataset. The results from UFastSLAM and the proposed approach are represented in (a) and (b), respectively. GPS results (black points) are also represented in these two figures. The control noises are σ_V=0.5m/s and σ_G=3°. The measurement noises are σ_r=0.1m and σ_φ=1°. Only three particles are used in the test.

Fig. 4 shows the robot trajectory results from UFastSLAM and the proposed UFastSLAM by overlapping the data obtained from GPS. In case of UFastSLAM, the robot trajectories are similar to the GPS result until the middle of the journey. However, the latter part of the robot journey shows numerous differences between two trajectories. The robot trajectory obtained from the proposed approach is more correctly estimated over time. In the latter part of the robot journey, the estimation result is remarkably consistent with GPS, meaning that the errors occurred from the particle depletion problem and the filter convergence problem are largely reduced using the weight compensation and particle formation maintenance schemes.

V. Conclusion

This paper presents an improved UFastSLAM using the geometric information of particles. The information is employed to compensate the assigned weights of particles and overcome the drawbacks of the resampling phase in the conventional UFastSLAM. The weights are compensated by the compensation scheme at first. Subsequently, the particle depletion problem occurred in the resampling part is eliminated by the particle formation maintenance scheme without any rejection or replication of particles. In the test, the proposed approach shows that its performance outperforms UFastSLAM in terms of the robot pose and the map.

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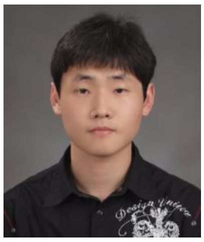

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