Rao-blackwellised Particle Filter SLAM with Consistent Mapping for AUVs

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***Abstract*—The particle filter has emerged as a useful tool for problems requiring dynamic state estimation. Recent years, people have been improving the particle filter algorithm constantly. The consistency of the algorithm has extremely important impact on the accuracy of the whole algorithm. In this paper, we propose an improved Rao-Blackwellized particle filter (RBPF) employing the First-Estimates Jacobian(FEJ) in the landmarks estimation of the particle filter to improve the accuracy of landmarks estimation, whereby a consistent mapping will be obtained, which can deservedly improve the consistency of the entire particle filter. The consistency problem of the algorithm is analyzed utilizing the normalized estimation error square(NEES), and the validity of the improved algorithm is verified by the sea trial using our own AUV platform, C-ranger.**

I. Introduction

The autonomous navigation capability called simultaneous localization and mapping (SLAM)[1], first proposed by Smith, Self and Cheeseman [2], can be described as a problem that a mobile robot is placed in an unknown environment and the robot incrementally builds a consistent map of this environment while simultaneously determining its location within this map[1]. Currently there are several popular SLAM algorithms: extended Kalman filter (EKF), sparse extended information filter (SEIF) and Rao-Blackwellized particle filter (RBPF) etc. Specially, RBPF has been more and more widely used owing to its fast and efficient characteristic.

The particle filter (PF) algorithm, first proposed by Arulampalam et al [3], is a kind of Monte Carlo method applying samples to present the probability density distribution, which can be employed to any state model, and when sample size tends to infinity, it can approximate any form of probability density distribution. Murphy et al. [4,5] introduced the Rao-Blackwellized particle filter as an effective means to solve the SLAM problem, which provides theoretical basis for the SLAM research using the particle filters more efficiently. The FastSLAM algorithm is a Rao-Blackwellized particle filter. However, according to the work by Bailey et al.[6], the FastSLAM algorithm cannot guarantee the consistency of robot pose estimation.

Guoquan Huang[7] analysed the reasons of the EKFs inconsistency from the perspective of observability, and proposed the First-Estimates Jacobian EKF(FEJ-EKF), which modified the contiguous items of the state transition matrix and the observation matrix and essentially changed the local observation matrix of EKF. And then verified the accuracy and coherence of FEJ-EKF through a large number of Monte Carlo simulation tests. In this paper, we innovatively apply this idea to the landmarks estimation in the particle filter, and use the observed values of the landmarks for the first time to update the map, which greatly improved the precision of the landmarks estimation and in turn improved the consistency of the particle filter. At last, we validate the algorithm through the sea trial.

II. Particle Filter algorithm with consistent mapping

A. Sample new pose

The vehicle pose are sampled conditioned on the motion model incorporating the most recent measurement data z_t and control input u_t, which can be denoted as:

$$S_t^n \sim p(s_t|\mathbf{s^{t-1,n}}, \mathbf{u^t}, \mathbf{z^t}, \mathbf{n^t}) \tag{1}$$

The new particles are distributed according to:

$$p(\mathbf{s^{t-1}}|\mathbf{u^{t-1}}, \mathbf{n^{t-1}}, \mathbf{z^{t-1}})p(s_t|\mathbf{s^{t-1}}, \mathbf{u^t}, \mathbf{z^t}, \mathbf{n^t}) \tag{2}$$

The distribution is referred to as the proposal distribution of particle filtering.

B. Update landmark estimation in each particle

The PF-SLAM represents the landmark estimates $p(\theta_i|\mathbf{s^t}, \mathbf{z^t}, \mathbf{u^t}, \mathbf{n^t})$ in (1) using EKFs. If the landmark is observed:

$$p(\theta_{i=n_t}|\mathbf{s^t}, \mathbf{z^t}, \mathbf{u^t}, \mathbf{n^t}) \propto p(z_t|\theta_{n_t}, s_t, n_t)p(\theta_{n_t}|\mathbf{s^{t-1}}, \mathbf{z^{t-1}}, \mathbf{u^{t-1}}, \mathbf{n^{t-1}}) \tag{3}$$

For $i \neq n_t$, the landmark posterior is unchanged:

$$p(\theta_{i\neq n_t}|\mathbf{s^t}, \mathbf{z^t}, \mathbf{u^t}, \mathbf{n^t}) \propto p(\theta_i|\mathbf{s^{t-1}}, \mathbf{z^{t-1}}, \mathbf{u^{t-1}}, \mathbf{n^{t-1}}) \tag{4}$$

C. First-Estimates Jacobian EKF

Guoquan Huang[7] reveals that it is possible to obtain an EKF system model with an unobservable subspace of dimension three, even if the Jacobians are not evaluated at the true state values. For this purpose, the following two changes are necessary.

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(A). Instead of computing the state-propagation Jacobian matrix Φ_{R_k}, we employ the expression:

$$\Phi'_{R_k} = \begin{bmatrix} I_2 & J(\widehat{P}_{R_{k+1|k}} - \widehat{P}_{R_{k|k-1}}) \\ 0_{1\times 2} & 1 \end{bmatrix} \tag{5}$$

Where $\widehat{P}_{R_{k+1|k}}$ is the estimated robot pose between time-steps k and k+1. The difference compared to traditional algorithm is that the robot position estimate prior to updating, $\widehat{P}_{R_{k|k-1}}$, is employed in this computation instead of the updated estimate, $\widehat{P}_{R_{k|k}}$.

(B).In the evaluation of the measurement Jacobian matrix H_{R_k} we always utilize the landmark estimate from the first time the landmark was detected. Thus, if a landmark was first seen at time-step l, we compute the measurement Jacobian with respect to the robot pose as:

$$H'_{R_k} = (\bigtriangledown h_k) C^T(\widehat{\phi}_{R_{k|k-1}})[-I_2 - J(\widehat{P}_{L_{l|l}} - \widehat{P}_{R_{k|k-1}})] \tag{6}$$

Where $\widehat{P}_{L_{l|l}}$ is the landmark pose that was first seen. This has as effect that the observability matrix N of this new filter, which we term First-Estimates Jacobian (FEJ)-EKF, assumes the form:

$$N' = \begin{bmatrix} -I_2 & -J(\widehat{P}_{L_{l|l}} - \widehat{P}_{R_{k|k-1}}) & I_2 \\ -I_2 & -J(\widehat{P}_{L_{l|l}} - \widehat{P}_{R_{k|k-1}}) & I_2 \\ .. & .. & .. \\ -I_2 & -J(\widehat{P}_{L_{l|l}} - \widehat{P}_{R_{k|k-1}}) & I_2 \end{bmatrix} \tag{7}$$

This matrix is of rank 2, and thus the FEJ-EKF is based on an error-state system model whose unobservable subspace is of dimension 3. The proposed algorithm performs better with respect to consistency, because when the filter Jacobians are calculated using the first-ever available estimates for each state variable, the error-state system model has the same observable subspace as the underlying nonlinear SLAM system. This is shown through the sea trials in section III.

D. Compute importance weight

The importance weight of each particle is calculated as follows:

$$\begin{aligned} w_t^n &= \frac{target \;\; distribution}{proposal \;\; distribution} \\ &= \frac{p(\mathbf{s^{t,n}}|\mathbf{z^t}, \mathbf{u^t}, \mathbf{n^t})}{p(\mathbf{s^{t-1,n}}|\mathbf{u^{t-1}}, \mathbf{n^{t-1}}, \mathbf{z^{t-1}})p(s_t^n|\mathbf{s^{t-1}}, \mathbf{u^t}, \mathbf{z^t}, \mathbf{n^t})} \end{aligned} \tag{8}$$

E. Importance resampling

After weighting each particle, the particles are then randomly sampled to form the new particle set to ensure that their probability of being resampled remains directly proportional to their normalized likelihood[8]. We introduce the effective number of particles in the resampling process to relieve particle degeneration. The effective number of particles is calculated by:

$$N_{eff} = 1/\sum_{i=1}^{N}(w_t^{[i]})^2 \tag{9}$$

Where N is the number of particles and w_t is the normalized weight. We set a threshold N_{min}, usually 75% of the number of particles, to determine whether the resampling process occurs or not.

III. Sea Trial Experiment in Tuandao Bay and Results Analysis

The experiment was performed at Tuandao Bay in Qingdao , China and the sea trial dataset was obtained from on-board sensors. A sonar operating with 120 scanning-sector and 120m maximum range is used to sense the environment, and features are extracted and used to build the global map of the environment based on the improved algorithm in previous sections. The satellite map (from Google Earth) and AUV trajectory measured by GPS are shown in Figure 1. In Figure 1, the red line obviously denotes the GPS trajectory of C-Ranger and a starting point with direction is marked with a green arrow.

Fig. 1. The satellite map of Tuandao Bay and the trajectory of C-Ranger by GPS.

A comparison of the trajectories for GPS, traditional Fast-SLAM and the FEJ-FastSLAM algorithm is shown in Figure 2. Obviously, the deviation of FEJ-FastSLAM (the blue line) relative to GPS is smaller than that of the traditional one (the green line).

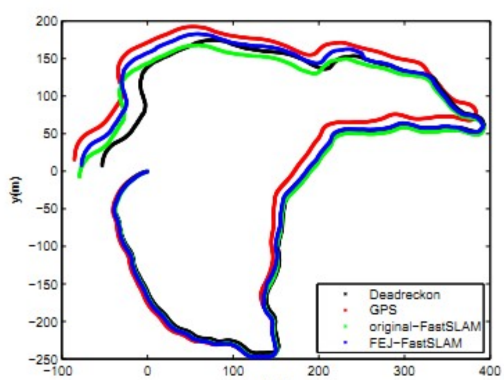

Fig. 2. Comparison of the trajectories for Deadreckon, GPS, traditional FastSLAM and the FEJ-FastSLAM algorithm.

The RMS errors of the traditional FastSLAM(the blue line) and the improved one(the red line) are shown in Figure 3. As we can see, the RMS error of the FEJ-FastSLAM is more satisfactory than the traditional one in the long term.

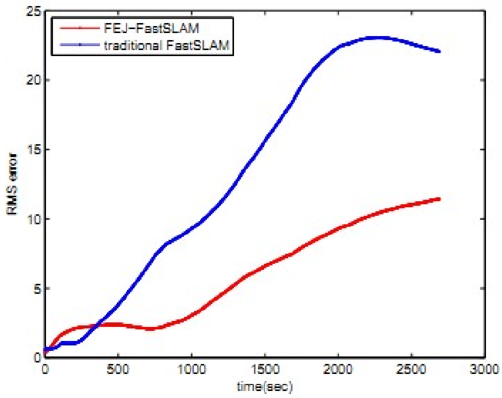

Fig. 3. RMS error of the FEJ-FastSLAM and the traditional FastSLAM.

The average NEES[6] of traditional FastSLAM and FEJ-FastSLAM are presented in Figure 4. It is obviously that the average NEES curve of FEJ-FastSLAM is bounded by the interval [2.36, 3.72] (the two green lines) and the traditional FastSLAM cannot. The results above validate the better performance of the FEJ-FastSLAM algorithm.

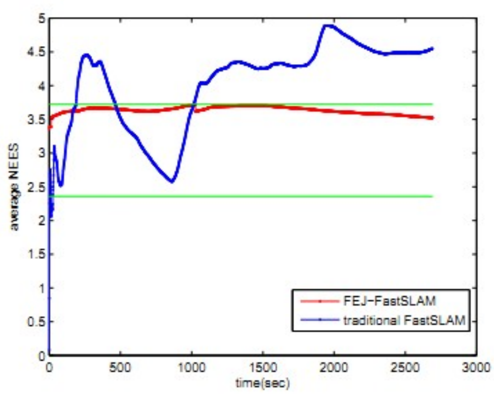

Fig. 4. Average NEES of the vehicle pose states over 50 Monte Carlo runs of the FEJ-FastSLAM and the traditional FastSLAM.

IV. Discussion

As is shown above, the FEJ-FastSLAM performs better than the traditional FastSLAM. The modified Jacobians are evaluated at the predicted value obtained at previous time-step instead of the estimated state value, which improves the accuracy of landmarks estimation and the average NEES of robot pose. At the same time, it maintains enough number of good particles by means of implementing effective number of particles.

As is mentioned in section I , the existing solutions of improving the consistency of PF-SLAM are mainly focused on resampling methods. In our future work, we will try to realize a combination improving both resampling methods and landmarks estimation proposed in this paper to refine the overall consistency of the PF algorithm. Improving resampling method can help to overcome the problem of particle degradation and meanwhile the FEJ-FastSLAM proposed in this paper will improve the mapping consistency. As a consequence, we have strong reasons to expect that the combined strategy will lead to a more satisfactory result.

V. Conclusion

In this paper, we proposed a novel FEJ-FastSLAM algorithm with mapping consistency for our own developed AUV platform C-Ranger. The refined FastSLAM algorithm produces better mapping consistency than the traditional one, which will deservedly help to improve the whole consistency of the FastSLAM. It employs the FEJ idea to update the landmarks, which improves the accuracy of landmarks estimation, and it also has the advantage of maintaining a diverse particle set by using the effective number of particles. Meanwhile, we have applied a fast sonar that can avoid fidelity compensation effectively in our C-Ranger platform. At last the sea trial and results reveal that the FEJ-FastSLAM implemented for the navigation of our AUV platform C-Ranger is actually more accurate and consistent compared with the traditional method.

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