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Procedia Computer Science 86 (2016) 261 – 264

Procedia Computer Science

2016 International Electrical Engineering Congress, iEECON2016, 2-4 March 2016, Chiang Mai, Thailand

Posterior Elimination Fast Look-Ahead Rao-Blackwellized Particle Filtering for Simultaneous Localization and Mapping

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Abstract

In this paper, a method for further reducing computation time for Fast Look-Ahead Rao-Blackwellized Particle filtering (Fast la-RBPF) for Simultaneous Localization and Mapping (SLAM) problem is presented. By using the pose posterior probability, states with low posteriors are excluded from the Kalman filtering updates to the computation time can be reduced. In conjunction with Fast la-RBPF, the proposed algorithm is then called the *Posterior Elimination Fast la-RBPF SLAM* algorithm. Simulation results show that the proposed method is more efficient in terms of computation time than Fast la-RBPF without any sacrifice in both localization and mapping error performances.

Peer-review under responsibility of the Organizing Committee of iEECON2016

Keywords: Probalistic Robotics, Simultaneous Localization and Mapping, Look-Ahead Rao-Blackwellized Particle Filter.

1. Introduction

In SLAM problems, Kalman filtering and its variants are used extensively as in the Extended Kalman Filter SLAM (EKF-SLAM) or RBPF in FastSLAM [1], [2]. Performance comparisons across different Kalman-based algorithms for SLAM have also been carried out. In [3], EKF-SLAM is compared versus FastSLAM whereas the

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Peer-review under responsibility of the Organizing Committee of iEECON2016
doi:10.1016/j.procs.2016.05.114

results showed that FastSLAM achieves superior accuracy than EKF-SLAM. In [4], a one step look-ahead (la) in RBPF for SLAM problem is proposed, the algorithm is then called the la-RBPF SLAM. The simulation results showed that la-RBPF can achieve higher accuracy in location and mapping than RBPF but the computation time of la-RBPF is much greater. In [5], a technique to reduce the computation time called Fast la-RBPF SLAM is proposed. In this paper, we propose a method for reducing computation time in Fast la-RBPF by using the posterior probabilistic criterion in the context of SLAM problems. The algorithm is then called the *Post Fast la-RBPF SLAM*. In [6], a similar technique is also used for reducing computation time for a particle filtering based algorithm but in the context of fault diagnosis in which the number of states to compute is much smaller than in SLAM. The simulation results for robot location errors, robot mapping errors and total computational times of the proposed algorithm at different number of particles compared with existing algorithms are shown in the simulation section.

NOTATION: The conditional probability distribution is denoted by $P(\cdot\,|\,\cdot)$, conditional probability density is denoted by $p(\cdot\,|\,\cdot)$ and conditional expectation operator is denoted by $E\{\cdot\,|\,\cdot\}$.

2. The Posterior Elimination on Fast la-RBPF for SLAM Algorithm

The importance weights of particle i^{th} in la-RBPF was developed in [5] by summation of the normal distribution of each possible robot pose

$$w_t^{[i]} = \sum_{z_t=1}^{n_z} \underbrace{N(\hat{y}_{t|t-1}^{[i]}(z_t), \hat{S}_t^{[i]}(z_t))p(z_t \mid z_{t-1}^{[i]}, y_{t-1})}_{\widehat{Post}(i,z_t)} \tag{1}$$

where $\hat{y}_{t-1}^{[i]}(z_t)$, $\hat{S}_{t-1}^{[i]}(z_t)$, $p(z_t \mid z_{t-1}^{[i]}, y_{t-1})$ and $\widehat{Post}(i,z_t)$ denote prediction measurement mean, prediction measurement covariance, robot pose prior and robot pose posterior respectively, and i^{th} represent each particles. n_z is number of total possible robot poses in constant map. The RBPF, la-RBPF, Fast la-RBPF and Post Fast la-RBPF use KF prediction step by the set of equation (3) for estimating the set of feature location (map) and set of feature observation

$$\begin{aligned}
\mu_{t|t-1}^{[i]} &= A(z_t^{[i]})\mu_{t-1|t-1}^{[i]} + F(z_t^{[i]})u_t, \\
\textstyle\sum_{t|t-1}^{[i]} &= A(z_t^{[i]})\textstyle\sum_{t-1|t-1}^{[i]} A(z_t^{[i]})^T + B(z_t^{[i]})B(z_t^{[i]})^T, \\
y_{t|t-1}^{[i]} &= C(z_t^{[i]})\mu_{t|t-1}^{[i]} + G(z_t^{[i]})u_t, \\
S_t^{[i]} &= C(z_t^{[i]})\textstyle\sum_{t|t-1}^{[i]} C(z_t^{[i]})^T + D(z_t^{[i]})D(z_t^{[i]})^T,
\end{aligned} \tag{2}$$

where $\mu_{t|t-1} \triangleq E\{x_t \mid y_{1:t-1}\}$ and $\sum_{t|t-1} \triangleq \mathrm{cov}(x_t \mid y_{1:t-1})$ are prediction mean and covariance of each features location, $y_{t|t-1} \triangleq E\{y_t \mid y_{1:t-1}\}$ and $S_t \triangleq \mathrm{cov}(y_t \mid y_{1:t-1})$ are prediction mean and covariance of each features observation. Next step is resampling step by using equation (2). And KF update or correction step by set of equation (3)

$$\begin{aligned}
K_t^{[i]} &= \textstyle\sum_{t|t-1}^{[i]} C(z_t^{[i]})^T S_t^{-1[i]}, \\
\mu_t^{[i]} &= \mu_{t|t-1}^{[i]} + K_t^{[i]}(y_t - y_{t|t-1}^{[i]}), \\
\textstyle\sum_t^{[i]} &= \textstyle\sum_{t|t-1}^{[i]} - K_t^{[i]} C(z_t^{[i]}) \textstyle\sum_{t|t-1}^{[i]},
\end{aligned} \tag{3}$$

where $K_t^{[i]}$ is Kalman gain, $\mu_t \triangleq E\{x_t \mid y_{1:t}\}$ and $\sum_t \triangleq \mathrm{cov}(x_t \mid y_{1:t})$ are mean and covariance of features location. For reduction in computation time in la-RBPF [5], when the robot pose posterior of any particle is the same as previous particles, previous mean and covariance are substituted without any KF computation in (3). In order to cope with the problem of too many small posteriors, two strategies have been proposed by means of thresholding as in [5] or by employing Gaussian kernel posterior elimination as in [7].

For *Post Fast la-RBPF SLAM*, we propose to further reduce the computation time by defining a using existing $\widehat{Post}(i-1,z_t)$ information for its prediction $\widehat{Post}(i,z_t)$. Any state with posterior poses lower than or equal to a