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Unscented H-infinity filtering based simultaneous localization and mapping with evolutionary resampling

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Abstract

Unscented FastSLAM (UFastSLAM) is a framework for simultaneous localization and mapping (SLAM). However, UFastSLAM is inconsistent over time due to the loss of particle diversity that caused mainly by the particle depletion in resampling step and incorrect a priori knowledge of process and measurement noise. To overcome these problems, in this paper, H-infinity UFastSLAM (HUFastSLAM) with evolutionary resampling is proposed. The proposed method can work in unknown statistical noise and does not require a prior knowledge about the of the noise statistics. In addition, to increase diversity, the resampling process is done based on the differential evolution (DE). The proposed algorithm is evaluated on a benchmark dataset. The simulation and experimental results demonstrate the effectiveness of the proposed algorithm in different situation.

1. Introduction

Simultaneous localization and mapping is one of the fundamental problems in mobile platform, which is a key prerequisite to truly autonomous robots. The two key computational solutions to SLAM are methods based on extended Kalman filter (EKF-SLAM) [1,2] and based on the Rao–Blackwellized particle filter (FastSLAM) [3]. However, EKF-SLAM algorithm suffers from some shortcomings such as computational complexity and data association that complicate their application to large environments for mobile robot [1,2].

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In order to solve these problems, based on the Rao–Blackwellized particle filter (RBPF) framework, a SLAM framework called FastSLAM is developed in [3]. In FastSLAM, particle filter is used to estimate the robot pose (position and heading of robot) and EKF is used to estimate the landmarks (features) location [3]. The advantage of this algorithm is that the data association decisions can be determined on a per-particle basis, and hence different particles can be associated with different landmarks [3]. The other advantage of FastSLAM is that particle filters can cope with nonlinear and non-Gaussian robot motion models [3]. FastSLAM2.0 linearizes the nonlinear model to improve the accuracy of a proposal distribution and employs the low-dimensional EKFs for estimating feature states. However, FastSLAM has some drawbacks that are derivation of the Jacobean matrices and the linear approximations of the nonlinear functions [4–7]. For solving these problems, a number of authors have proposed UFastSLAM [4–7]. In UFastSLAM, the linearization process with Jacobian calculations is removed by applying the unscented transformation (UT) [8,9]. The main advantage of UFastSLAM is that it does not use the derivation of the Jacobian matrices and the linear approximations to the nonlinear functions. However, since UFastSLAM employs the resampling process, it only can be achieved consistently for longer time periods [6]. There are two main sources for inconsistency of UFastSLAM: first, the performance of UFastSLAM depends on correct a priori knowledge of the process and measurement noise that are unknown in real-life applications. An incorrect a priori knowledge may seriously degrade the performance of UKF [10–12] and consequently UFastSLAM. It can even lead to practical divergence and inconsistency [10–12].

In filtering field, a classical method for solving this problem is adaptive estimation of priori knowledge. Several research works have been reported in the direction, which have attempted adaptive estimation of priori knowledge. In [10,11], a pioneering work on adaptive estimation of noise covariance matrices for Kalman filtering algorithm based on correlation-innovations method is reported. In [12,13], adaptive unscented Kalman filter is presented. Researchers used from this idea for EKF-SLAM application [14,15]. These papers propose a neuro-fuzzy based adaptive Kalman filter algorithm for SLAM. This algorithm starts with unknown statistics and then adapts them, on the basis of a neuro-fuzzy system that attempts to minimize the mismatch between the theoretical and the actual values of the innovation sequence. The free parameters of the neuro-fuzzy system are learned by employing particle swarm optimization in learning step. A limitation of this algorithm is that, it is needed to learn its free parameters under off line situation.

Other classical method for solving this problem is H-infinity filtering [16–19]. Compared to the Kalman filter that requires an exact and an accurate system model as well as a perfect knowledge of the noise statistics, the H-infinity filtering requires no a prior knowledge of the noise statistics. In particular, unlike the Kalman filter that aims to give the minimum mean-square estimate, the H-infinity filtering minimizes the effect of the worst possible disturbances on the estimation errors and hence it is more robust against model uncertainty. Although H-infinity estimation techniques have been studied in many fields such as signal reconstruction [20], nonlinear systems [21] and switched systems under asynchronous switching [22], there are a few searches on H-infinity filtering in FastSLAM application. In [23], authors present H_∞ FastSLAM framework. As H_∞ FastSLAM adopts the idea of FastSLAM, the inherent disadvantages associated with FastSLAM, such as lower nonlinearity requirements of the nonlinear functions and the computation errors of Jacobian matrices, remains a challenge to overcome.

Second, in general, a property of UFastSLAM is that the variance of sample weights increases over time, that is to say, the particle degeneracy phenomenon is unavoidable. To solve this problem, the resampling is performed. Its basic idea is to eliminate low-weight particles and