Robust Adaptive Central Difference Particle Filter

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ABSTRACT

This paper presents a new robust adaptive central difference particle filtering method for nonlinear systems by combining the concept of robust adaptive estimation with the central difference particle filter. This method obtains system state estimate and covariances using the principle of robust estimation. Subsequently, the importance density is obtained by adjusting the state estimate and covariances through the equivalent weight function and adaptive factor constructed from predicted residuals to control the contributions to the new state estimation from measurement and kinematic model. The proposed method can not only minimize the variance of the importance density distribution to resist the disturbances of systematic noises, but it also fully takes advantage of present measurement information to avoid particle degeneration. Experiments and comparison analysis with the existing methods demonstrate the improved filtering accuracy of the proposed method.

Keywords: *Adaptive Factor, Central Difference Particle Filter, Equivalent Weight Function, Robust Adaptive Filter*

1. INTRODUCTION

The problem of nonlinear filtering has its origins in the areas of tracking and signal processing. Nevertheless, the underlying setting is extremely general and is ubiquitous in many applied areas such as integrated navigation system, geodetic positioning and automatic control, where random processes are used to model complex dynamical phenomenon. In essence, nonlinear filtering is to estimate the state of a nonlinear and non-Gaussian stochastic system from measurement data. However, this process inevitably involves a gross error when there is a deviation between theoretical and actual models, leading to the biased or even divergent filtering solution.

This paper presents a new robust adaptive central difference particle filtering (RACDPF)

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method for the problem of nonlinear filtering. This method incorporates the concept of robust estimation in the central difference particle filter (CDPF) to resist the influence of systematic noises on system state estimation. It obtains system state estimate and associated covariances via robust estimation, and further obtains the importance density function using the robust equivalent weight and adaptive factor. The obtained importance density function fully takes the advantage of present measurement information to avoid particle degeneration. Through the robust equivalent weight function and adaptive factor, the variance of the importance density distribution is minimized to resist the disturbance of systematic noise, thus improving the filtering accuracy. Experiments and comparison analysis have been conducted to comprehensively evaluate the performance of the proposed filtering method.

2. RELATED WORK

A significant amount of research efforts have been dedicated to the problem of nonlinear filtering. The extended Kalman filter (EKF) is an approximation method, in which nonlinear system equations are linearized by the Taylor series and the linear states are assumed to obey the Gaussian distribution. The linearization stage of the state equations may lead to the problem of divergence or instability (Cappe, Godsill, & Moulines, 2007). The EKF also requires the calculation of Jacobian matrix, which is a difficult and time-consuming process. Jacobian matrix may not even exist in some cases.

The unscented Kalman filter (UKF) and central difference Kalman filter (CDKF) are belonged to a single family of non-derivative Kalman filters. Both are based on statistical approximations of system equations without requiring the calculation of Jacobian matrix. Therefore, they have the higher accuracy and convergent speed than the EKF. The UKF combines the concept of unscented transform with the linear update structure of the Kalman filtering. However, it considers the second-order system momentum only, leading to the limited accuracy (Cappe, Godsill, & Moulines, 2007; Sarkka, 2007; Del Moral, Doucet, & Jasra, 2006; van der Merwe, Doucet, de Freitas, & Wan, 2000; Tenne, & Singh, 2003; Gordon, Salmond, & Smith, 1993). The CDKF approximates the state estimation and covariances of stochastic variables through central difference transformation. Its approximation accuracy is at least in the second order, leading to the higher filtering accuracy than the UKF. The CDKF also has a much simple structure than the UKF, as only one single scaling parameter is required for the CDKF while three parameters for the UKF. However, both CDKF and UKF require the system state obey the Gaussian distribution. Further, if the nonlinearity of a dynamic system is strong, both will lead to the biased or even divergent filtering solution (Simon, 2006).

The particle filter (PF) is an optimal recursive Bayesian filtering method based on Monte Carlo simulation to produce a sample of independent random variables distributed according to the given probability distribution. This method can deal with nonlinear system models and non-Gaussian noise, and is easy to implement, even for high-dimension problems. It can also handle the singularities of measurement information (Oppenheim, Philippe, & de Rigal, 2008; Cody, Dieter, & Marina, 2004). However, the phenomenon of particle degeneracy may occur in the approximation process, and the accuracy largely depends on the choice of the importance sampling density and resampling scheme. Various methods were studied, aiming at designing an appropriate importance sampling density or modifying the resampling scheme to improve the performance of the particle filter. Resampling is one of the earliest methods to deal with the problem of particle degeneracy (Kotecha, & Djuric, 2003; Arulampalam, Maskell, Gordon, & Clapp, 2002; Johansen, & Doucet, 2008; Doucet, de Freitas, Murphy, & Russell, 2000; Julier, & LaViola, 2007; Liu & Chen, 1998). The importance sampling improves the resampling method by adopting an important density function to the resampling process (Srinivasan, 2002). However, the resampling and importance sampling methods result in the loss of diversity among

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