Robust Adaptive Unscented Particle Filter

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ABSTRACT

This paper presents a new robust adaptive unscented particle filtering algorithm by adopting the concept of robust adaptive filtering to the unscented particle filter. In order to prevent particles from degeneracy, this algorithm adaptively determines the equivalent weight function according to robust estimation and adaptively adjusts the adaptive factor constructed from predicted residuals to resist the disturbances of singular observations and the kinematic model noise. It also uses the unscented transformation to improve the accuracy of particle filtering, thus providing the reliable state estimation for improving the performance of robust adaptive filtering. Experiments and comparison analysis demonstrate that the proposed filtering algorithm can effectively resist disturbances due to system state noise and observation noise, leading to the improved filtering accuracy.

Keywords: Adaptive Factor, Equivalent Weight Function, Particle Filter, Robust Adaptive Filtering, Unscented Particle Filter, Unscented Transformation

1. INTRODUCTION

The problem of nonlinear filtering is common in many areas such as integrated navigation system, geodetic positioning, automatic control, information fusion and signal processing. The extended Kalman filtering is a commonly used filtering method to nonlinear systems (Julier, Uhlmann & Durrant-Whyte, 2000; Lefebvre, Bruyninckx & Schutter, 2004). This is an approximation method, in which nonlinear system equations are linearized by the Taylor expansion and the linearized states are assumed to obey the Gaussian distribution. The linearization stage of the state equations may lead to a problem of divergence or instability (Simon, 2006). Especially, when the practical probability function has multiple peak values, the estimated state error is very large or even divergent (Grewal & Andrews, 2008). The unscented Kalman filtering (UKF) method combines the concept of unscented transform with the Kalman filtering (Julier & Uhlmann, 2004; Wan & van der Merwe, 2000). This method inherits the linear update structure of the Kalman filtering. It uses only the second-order system moments, which may not be sufficient for some nonlinear systems.

The particle filtering (PF) is an optimal recursive Bayesian filtering method based on
Monte Carlo simulation (Doucet, Godsill & Andrieu, 2000; Rawlings & Bakshi, 2006). This method aims to produce a sample of independent random variables distributed according to the conditional probability distribution. It is not limited by the linearized errors and the assumption of Gaussian noise, and thus can deal with nonlinear system models and non-Gaussian noise (Rawlings & Bakshi, 2006). It is also easier to implement, even for high dimensional problems. Therefore, particle filtering has been widely used in the fields of navigation, target tracking, fault detection, robotic control and computer vision (Zhang, Chen, Zhou & Li, 2007; Oppenheim & Philippe & de Rigal, 2008).

However, the accuracy of the PF method largely depends on the choice of importance sampling density and resampling scheme (Yang, Tian, Jin & Zhang, 2005; Arulampalam, Maskell, Gordon & Clapp, 2002; Watzenig, Brandner & Steiner, 2007). Recently, various methods have been proposed to design a good importance sampling density or modify the resampling scheme (Yang, Tian, Jin & Zhang, 2005; Arulampalam, Maskell, Gordon & Clapp, 2002; Watzenig, Brandner & Steiner, 2007).

The unscented particle filtering (UPF) method uses unscented transformation to get a better importance sampling density (van der Merwe, Doucet, Freitas & Wan, 2000; Liang, Ma & Dai, 2008; Ning & Fang, 2008; Ali & Fang, 2009). The unscented transformation calculates the statistics of a random variable that undergoes a nonlinear transform (Julier & Uhlmann, 2004). It enables the estimation of state mean and variance to achieve the third-order accuracy, thus providing higher accuracy for filtering. However, the particle degeneracy phenomenon could occur if a dynamic system has very small noise or the observational noise has very small variance (Oppenheim & Philippe & de Rigal, 2008; Ning & Fang, 2008; Ali & Fang, 2009). In fact, it is unavoidable in practical engineering applications that a dynamic system has small systematic noise due to the disturbances caused by singular observations and uncertain factors.

The robust adaptive filtering is a method to deal with observation and model noises by robustly estimating the covariance matrix of observation noise and adaptively adjusting the covariance matrix of the state noise through the adaptive factor (Yang & Cui, 2008; Gao, Zhong & Li, 2011). It combines the merits of both robust estimation and adaptive filtering. It cannot only augment additional parameters into the covariance matrix of the state prediction from the Kalman filtering model to compensate the systematic model errors, but it can also obtain reliable filtering results by using robust estimation principles for observation information, especially in the presence of singular observations.

Yang et al. reported a robust adaptive filter by combining the robust maximum-likelihood estimation with the adaptive filtering process to adaptively adjust the weight matrix of predicted parameters according to the difference between system observation and model information (Yang, He & Xu, 2001; Yang & Gao, 2006). This filter can be adaptively converted into the classical Kalman filter, adaptive Kalman filter, and Sage filter by modifying the weight matrix and adaptive factor. However, when the observational information is insufficient at certain epochs, it is difficult to estimate state parameters at these epochs. The filter was also extended to the case with multiple adaptive factors (Yang & Cui, 2008; Geng & Wang, 2008). Although the robustness is improved by using multiple adaptive factors, this method causes an extra computational load, as it requires the number of observations at all calculation epochs be larger than the number of state components. Ding et al. (2007) reported a process noise scaling method to improve the robustness of adaptive filtering. This method monitors the status of the filter operation by using covariance matching. However, it cannot optimally distribute noises to each individual source. Gao, Zhong & Li (2011) studied the application of the robust adaptive filter in integrated navigation system. However, this method may not guarantee that the robust adaptive factor constructed based on predicted residuals is optimal for achieving...
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