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Stochastic stability of sigma-point Unscented Predictive Filter

Lu Cao [a,*], Yu Tang [b,1], Xiaoqian Chen [b,2], Yong Zhao [b,3]

[a] The State Key Laboratory of Astronautic Dynamics, China Xi'an Satellite Control Center, Xi'an 710043, China
[b] College of Aerospace Science and Engineering National University of Defense Technology, Changsha 410073, China

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ABSTRACT

In this paper, the Unscented Predictive Filter (UPF) is derived based on unscented transformation for nonlinear estimation, which breaks the confine of conventional sigma-point filters by employing Kalman filter as subject investigated merely. In order to facilitate the new method, the algorithm flow of UPF is given firstly. Then, the theoretical analyses demonstrate that the estimate accuracy of the model error and system for the UPF is higher than that of the conventional PF. Moreover, the authors analyze the stochastic boundedness and the error behavior of Unscented Predictive Filter (UPF) for general nonlinear systems in a stochastic framework. In particular, the theoretical results present that the estimation error remains bounded and the covariance keeps stable if the system's initial estimation error, disturbing noise terms as well as the model error are small enough, which is the core part of the UPF theory. All of the results have been demonstrated by numerical simulations for a nonlinear example system.
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1. Introduction

The real-time predictive filter is a widely used method in many application areas, such as spacecraft attitude determination [1–5], chaotic synchronization system [6], inertial alignment system, etc. It provides a way of determining optimal state estimates in the presence of significant error in the assumed (nominal) model, which is first introduced by Lu [7,8] and further developed by Crassidis and Markley [9–11]. The algorithm can be implemented in real time to estimate the model error online. Because the model errors are not restricted only to Gaussian noise, it is manifest that the PF is more general than other nonlinear estimate methods, such as the extended Kalman filter. In essential, the PF owns the advantages of both the Kalman filter (i.e., a real-time estimator) and the Minimum Model Error (MME) [1] estimator (i.e., determines actual model error trajectories), which includes: (1) the model error and process noise are assumed unknown and are estimated as part of the solution; (2) the model error may take any form (even nonlinear); (3) the algorithm can be implemented online to measure filter noisy as well as to estimate state trajectories; (4) the algorithm is robust in the presence of high noise measurement. Generally, it works better than other nonlinear estimate methods, such as the extended Kalman filter, so it has attracted a lot of attention from researchers.

However, the PF still has some serious disadvantages remaining to be improved. According to the theoretical analyses of the PF, the estimate model error is only accurate to the first order of the posterior mean, which will introduce serious errors into the state estimate with the estimate model errors. Therefore, it will inevitably bring some problems, such as the loss of the estimate precision, slow rate of convergence, etc. If the estimate model error is deviated largely from its actual value, the error will be propagated by the state equation to amplify the error effect, resulting in filter divergent. With a view to tackle the shortcomings mentioned above, an alternative is needed. The Unscented Predictive Filter (UPF) is derived through the use of minimal set of deterministically chosen sigma points based on UT technique [12–16]. These sigma points completely have the same mean and covariance to the system state distribution. When these points are propagated through the nonlinear model error functions, the sigma points can capture the higher estimate accuracy of the model error. Theoretical analyses of the estimate model error for the UPF are demonstrated to capture the posterior mean accurately up to the 3rd order for nonlinear Gaussian system, with errors only introduced in the 4th and high orders. At the same time, the estimate model error can capture the posterior mean accurately to the 2nd order for any nonlinearity, which is better than the accuracy of the classical PF. This derivativeless based

* Corresponding author.
E-mail addresses: caolu_space2015@163.com, caolu0206@gmail.com (L. Cao), tangyu55@gmail.com (Y. Tang), chenxiaoqian@nudt.edu.cn (X. Chen), nudtzhy@gmail.com (Y. Zhao).
[1] Tel.: +86 13786109400.
[2] Tel.: +86 13975161530.
[3] Tel.: +86 13786143694.

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on predictive filter consistently outperforms the PF not only in terms of estimate accuracy, but also in filter robustness and easy implementation. Therefore, the UPF can make up for the deficiencies of the PF sufficiently and intensify the practicability of the UPF.

Without loss of generality, a study of a more general nonlinear case in a stochastic framework would also be of some interest, which is the core of the UPF theory. We obtain the stability results for more general nonlinear estimation problems by analyzing the error behavior of the UPF. Particularly, it is proved that the estimate error remains bounded and the covariance keeps stable if the system's initial estimation error, the disturbing noise terms as well as the model errors are small enough, which consist of the main contributions.

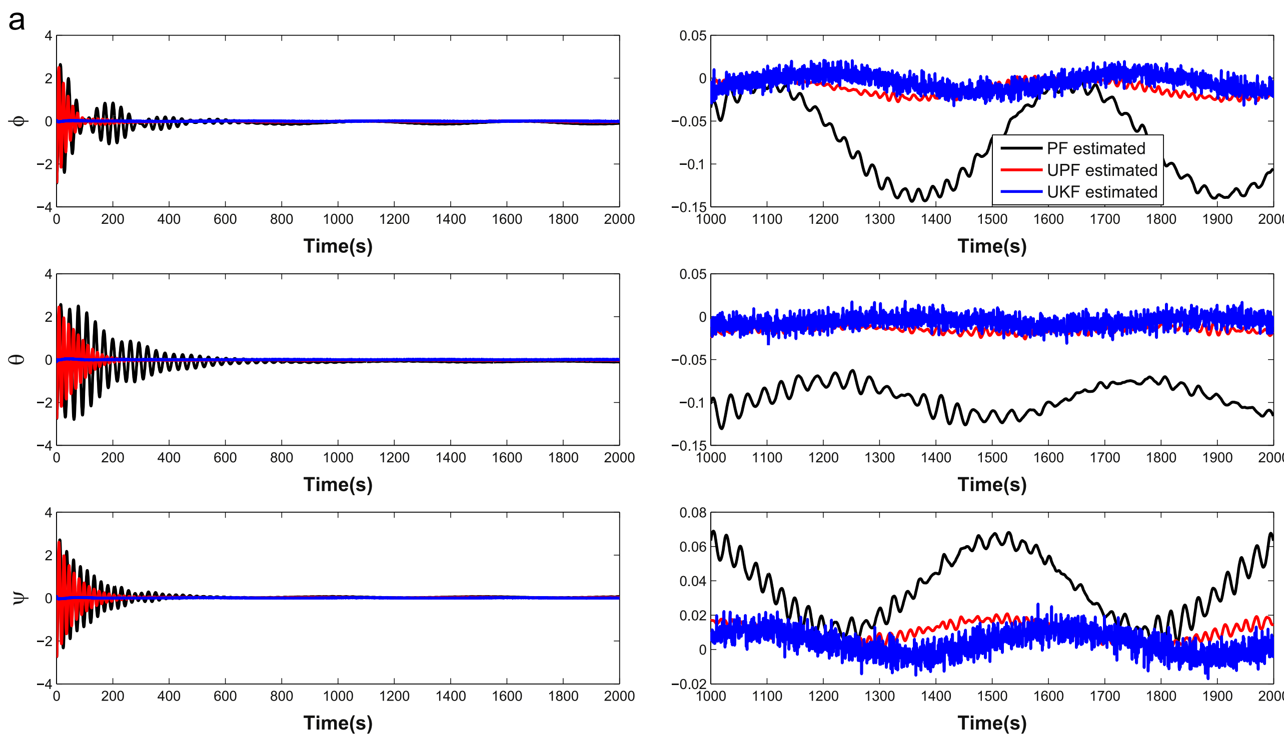

Fig. 1. Numerical simulations for the nominal case: (a) the estimation error of the angular; (b) the estimation error of the angular velocity; (c) the estimation of the model error.

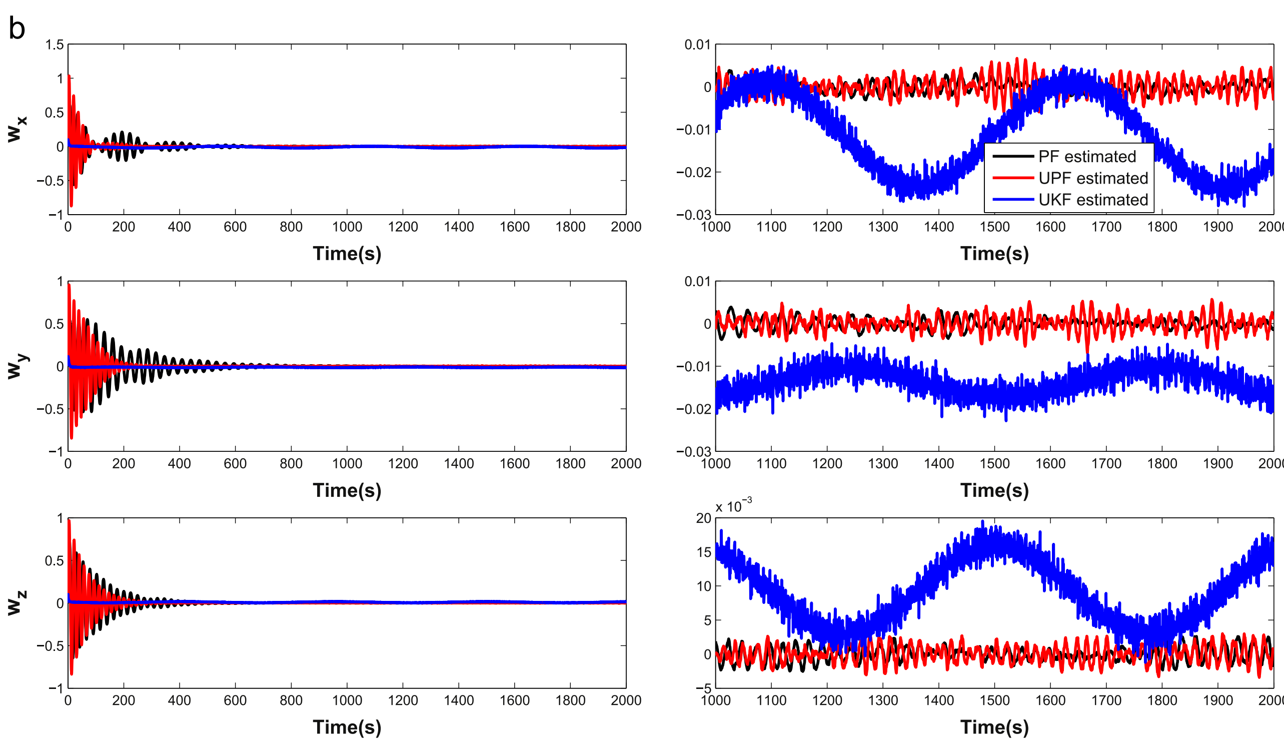

Fig. 1. (*continued*)

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