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Covariance matching based adaptive unscented Kalman filter for direct filtering in INS/GNSS integration

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ABSTRACT

The use of the direct filtering approach for INS/GNSS integrated navigation introduces nonlinearity into the system state equation. As the unscented Kalman filter (UKF) is a promising method for nonlinear problems, an obvious solution is to incorporate the UKF concept in the direct filtering approach to address the nonlinearity involved in INS/GNSS integrated navigation. However, the performance of the standard UKF is dependent on the accurate statistical characterizations of system noise. If the noise distributions of inertial instruments and GNSS receivers are not appropriately described, the standard UKF will produce deteriorated or even divergent navigation solutions. This paper presents an adaptive UKF with noise statistic estimator to overcome the limitation of the standard UKF. According to the covariance matching technique, the innovation and residual sequences are used to determine the covariance matrices of the process and measurement noises. The proposed algorithm can estimate and adjust the system noise statistics online, and thus enhance the adaptive capability of the standard UKF. Simulation and experimental results demonstrate that the performance of the proposed algorithm is significantly superior to that of the standard UKF and adaptive-robust UKF under the condition without accurate knowledge on system noise, leading to improved navigation precision.

1. Introduction

The INS/GNSS (Inertial Navigation System/Global Navigation Satellite System) integration has proven to be a very efficient means of navigation due to the short term accuracy of INS allied with the long term accuracy of GNSS [1–6]. According to the differences of estimated system state, the existing studies on using the Kalman filtering for INS/GNSS integrated navigation can be divided into two categories, i.e. the direct and indirect approaches [7,8]. The indirect approach takes the navigation errors of the subsystems INS and GNSS as the system state, and calculates its optimal estimates. The direct approach uses the output navigation parameters of the subsystems as the system state, and directly obtains the navigation solution of the integrated system by Kalman filtering. Compared to the indirect method, the direct approach has the following advantages [9,10]: (i) The system state equation directly describes the dynamic process of navigation parameters, which exactly reflects the evolution of the real state and is more accurate than the first-order approximation of the indirect method; (ii) Since the mechanical calibration equation of INS is the key component of the system state equation, the Kalman filtering does not only achieve the navigation solution from the mechanical calibration equation, but it also plays a role of filtering estimation, avoiding a great amount of repetitive calculations. However, the use of the direct approach for

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INS/GNSS integrated navigation introduces nonlinearity into the system state equation, making the traditional linear Kalman filter (KF) no longer suited to deal with the nonlinearity involved in the direct filtering [4,11,12].

The extended Kalman filter (EKF) is the commonly used algorithm for state estimation of a nonlinear system [13–16]. It is an approximation method, in which nonlinear system equations are linearized by the Taylor expansion such that the KF can be applied. However, the first-order linearization of the state equations causes large error for the posterior mean and covariance of the state vector, and the Jacobian matrix may not even exist in some cases [12,13]. The unscented Kalman filter (UKF) is proposed as an improvement to the EKF [17–21]. It uses a finite number of sigma points to propagate the probability of state distribution through nonlinear system dynamics. The UKF can capture the posterior mean and covariance of the state of any Gaussian and nonlinear system in third-order accuracy. It can also avoid the cumbersome evaluation of Jacobian matrices, making the algorithm easier to implement [19]. Due to these merits, the UKF has received great attention [6,9,21–25]. However, similar to the EKF, the use of the standard UKF for system state estimation requires the accurate priori knowledge on the characteristics of process and measurement noises. Particularly, the uncertainty in system noise has a crucial impact on the standard UKF and may result in the significantly degraded performance [26]. In practice, due to the uncertainties in the dynamic environment and the limitation of test samples, it is difficult to accurately describe the noise statistics of inertial instruments and GNSS receivers, leading to sub-optimal or even divergent navigation solutions. Therefore, it is absolutely necessary to make full use of the information obtained in the filtering process for resisting the disturbance of system noise error on system state estimation.

Adaptive Kalman filtering is a method to resist the influence on the filtering solution due to inaccurate statistics of system noise [27–30]. Various adaptive UKFs have been developed using different scenarios of adaptation. Cho and Choi presented a sigma-point based receding-horizon Kalman filter (SPRHKF). This filter improves the standard UKF by using the receding horizon strategy to adaptively resist model uncertainty and temporarily unknown sensor bias [31]. However, due to the use of a finite impulse response structure, the filtering convergence is poor. Cho and Kim developed an adaptive fusion filter by combining the UKF and SPRHKF through an interactive multi-model (IMM) estimator. This filter overcomes the defects of both the UKF and SPRHKF [32]. However, it causes an expensive computational load, unable to achieve the real-time performance. Wang presented an adaptive-robust UKF (ARUKF) by introducing adaptive factors into the robust UKF [33]. This filter can weaken the effect of the uncertainty of the system models on the Kalman filtering accuracy. However, as the equivalent weight factors and the adaptive factors are determined empirically, the ARUKF cannot be adapted to the changing conditions.

Studies were also reported focusing on online estimation of system noise statistics rather than correcting them in the filtering process. These studies can be classified into four categories [27,34]: the Bayesian, maximum likelihood, covariance matching and correlation methods. The Bayesian and maximum likelihood methods require intensive computations and both are based on the assumption that the dynamic error is time-invariant, thus unsuitable for INS/GNSS integration [26,35]. The correlation method is common for estimation in time series analysis. This method correlates system output either directly or after a known linear operation. However, it is mainly suitable for a linear system with constant coefficients [36,37], and cannot be used for a nonlinear filter.

The covariance matching is an adaptive technique to estimate the covariances of process and measurement noises at every sampling instant by keeping the elements of innovation covariance or residual covariance consistent with their theoretical values [38,39]. Using the historical data of state prediction and state estimation, the sample covariances of residual and innovation sequences are computed cumulatively based on the data either in the entire history or in a moving time window. Process noise covariance and measurement noise covariance are then estimated from the obtained sample covariances. The covariance matching technique is intuitive and can be extended to the UKF to improve the performance of state estimation in the presence of biased priori noise statistics. This improvement can be achieved at a modest computational cost by adopting the limited memory procedure, making the covariance matching technique suitable for the purpose of real-time computation [27].

This paper presents a new covariance matching based adaptive unscented Kalman filter (CMAUKF) for INS/GNSS integrated navigation system. On the basis of the covariance matching technique, a noise statistic estimator is designed to online update the covariance matrices of process and measurement noises, and subsequently feed them back to the standard UKF to compensate the priori knowledge of noise distribution in INS and GNSS. The proposed method enhances the adaptive capability of the standard UKF for active state and parameter estimations. The performance of the INS/GNSS integrated system designed using the proposed CMAUKF was verified through simulations and practical experiments.

2. Standard UKF

In order to show the improvement of the proposed method over the standard UKF clearly, let us briefly review the concept of the standard UKF at first.

Consider the following nonlinear discrete stochastic system

$$\begin{cases} \boldsymbol{X}_k = f(\boldsymbol{X}_{k-1}) + \boldsymbol{w}_k \\ \boldsymbol{Z}_k = \boldsymbol{H}_k \boldsymbol{X}_k + \boldsymbol{v}_k \end{cases} \tag{1}$$

where $\boldsymbol{X}_k \in \boldsymbol{R}^n$ is the state vector at discrete time k, $\boldsymbol{Z}_k \in \boldsymbol{R}^m$ is the measurement vector, $\boldsymbol{w}_k \in \boldsymbol{R}^n$ and $\boldsymbol{v}_k \in \boldsymbol{R}^m$ are the additive process noise and measurement noise, the nonlinear function $f(\cdot)$ describes the process model, and $\boldsymbol{H}_k$ is the measurement matrix.