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Robust weighted fusion time-varying Kalman smoothers for multisensor system with uncertain noise variances

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ABSTRACT

This paper addresses the design of robust weighted fusion time-varying Kalman smoothers for multisensor time-varying system with uncertain noise variances by the augmented state approach. According to the minimax robust estimation principle and the unbiased linear minimum variance (ULMV) optimal estimation rule, the six robust weighted fusion time-varying Kalman smoothers are presented based on the worst-case conservative system with the conservative upper bounds of noise variances. The actual smoothing error variances of each fuser are guaranteed to have a minimal upper bound for all admissible uncertainties. Their robustness is proved by the Lyapunov equation approach. Their robust accuracy relations are analyzed and proved. Specially, the corresponding steady-state robust Kalman smoothers are also presented for multisensor time-invariant system, and the convergence in a realization between the time-varying and steady-state robust Kalman smoothers is proved by the dynamic error system analysis (DESA) method and dynamic variance error system analysis (DVESA) method. A simulation example is given to verify the robustness and robust accuracy relations.

1. Introduction

The multisensor data fusion is how to combine the local measurement data or local state estimators to obtain a global fused state estimator with higher accuracy than those of the local state estimators [14]. It has been widely applied in many fields including defense, target tracking, signal processing, GPS positioning, unmanned aerial vehicle (UAV), remote sensing, communication, command, control, computer, and intelligent (C^4I) systems [3,12,18], and has attracted significant interest in recent years. There are two basic fusion approaches: the centralized and distributed fusion approaches, depending on whether raw data are used directly for fusion or not. The former can give a globally optimal state estimate by communicating all the measurement data from the local sensors to the fusion center. However, its computation and communication burden is larger. The latter can be classified as the state fusion and measurement fusion approaches. The state fusion approach can give a global optimal or suboptimal fused state estimate by combining or weighting the local state estimators, its advantages are that the computation and communication burden can be reduced and it can facilitate fault detection and isolation, and has stronger fault-tolerance. Under the unbiased linear minimum variance (ULMV) optimal estimation rule, there are three global suboptimal weighted state fusion approaches weighted by matrices, scalars and diagonal matrices respectively [6,34,35]. The measurement fusion approach can give a global optimal fused state estimate by weighting the local

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measurement data and only less computation burden is required. Based on the weighted least squares (WLS) method, two weighted measurement fusion approaches are presented in [11,13,29].

The Kalman filtering [2,19] is a basic tool of multisensor data fusion, it is only suitable for the systems with exactly known model. For uncertain systems with the uncertainties of model parameters and/or noise variances, the performance of the Kalman filter will degrade or the filter may be divergent [22]. In order to overcome this limitation, the research of the robust Kalman filters received great attention. Up to now, many references of the robust Kalman filters mainly consider the systems with the model parameters uncertainties. An important class of the robust Kalman filtering problems is to find a Kalman filter such that its actual filtering error variances yielded by all admissible uncertainties are guaranteed to have a minimal upper bound [9,15,22,23,43,44,46]. Such a Kalman filter is called robust Kalman filter, and such property is called robustness. There are two main approaches to solve this problem, i.e., the Riccati equation approach [22,23,43,44,46] and the linear matrix inequality (LMI) approach [9,15,22,31,39,40,42], where the finite-horizon (time-varying) robust Kalman filters were presented in [23,28,33,38,46], and the infinite-horizon (steady-state) robust Kalman filters were presented in [23,46]. These researches [9,15,22,24,43,44,46] on the robust Kalman filters have the limitation that only the model parameters are uncertain, while the noise variances are known exactly. For the uncertain systems with uncertainties of noise variances, the robust Kalman filters are seldom presented [41,45]. A minimax robust Kalman filter was presented for descriptor system with single sensor [41]. A robust Kalman filter was presented by the Riccati equation approach for system with uncertain parameters and noise variances [45]. The information fusion robust Kalman filters are seldom considered, and the robustness of the fused Kalman filters was not proved [1,4,10]. Recently, based on the minimax robust estimation principle [27], the robust weighted fusion time-varying and steady-state Kalman filters with uncertain noise variances have been presented, whose robustness is rigorously proved by the proposed Lyapunov equation method [24], where the robust weighted fusion steady-state Kalman filters are obtained by the indirect approach of taking the limit operations to the robust weighted time-varying Kalman fusers, and they can also be obtained by the direct approach based on the steady-state Kalman filtering theory [25]. The robust weighted fusion Kalman predictors with uncertain noise variances have been presented in [26]. However, the robust weighted fusion Kalman smoothing problem was not solved.

In order to develop the robust information fusion Kalman filtering theory [24–26], in this paper, we will present the robust weighted fusion time-varying Kalman smoothers for multisensor time-varying system with uncertain noise variances. Applying the standard Kalman smoothing algorithm (non-augmented state approach) [19] to solve this problem has some difficulties. The main difficulties are the computation of the local smoothing error cross-covariances and the robustness analysis. Therefore, according to the minimax robust estimation principle [27], under the ULMV and WLS optimal estimation rules, applying the augmented state approach, the local and weighted fusion robust time-varying Kalman smoothers will be presented based on the worst-case conservative system with the conservative upper bounds of noise variances. They include six robust weighted fusers, namely three robust state fusers weighted by matrices, diagonal matrices and scalars, two robust weighted measurement fusers and a modified robust covariance intersection (CI) fuser.

The above three weighted state fusion approaches need to compute the cross-covariances among the local Kalman smoothers [6,8,35], but in many practical applications, the correlations or cross-covariances of the local estimates are unknown [16–18], or the cross-covariances are very complicated [36,37] or their computation burden is larger [36]. In order to solve these problems, the covariance intersection (CI) fusion method was presented [16–18]. Its advantages are that the cross-covariances can be unknown or uncertain, and the computation of the cross-covariances can be avoided. Its disadvantages are that the conservative estimates of the actual local state estimation error variances are assumed to be known, and it gives a conservative upper bound of the actual fused estimation error variances. In order to overcome these disadvantages, in this paper, a modified robust CI fusion Kalman smoother with conservative cross-covariances information is presented based on the proposed local robust Kalman smoothers. Not only it can give the conservative estimates of the actual local state estimation error variances, but also it can give a minimal upper bound of the actual CI fused smoothing error variances. Recently, the ellipsoidal intersection (EI) fusion method with cross-covariances information [32] was presented, which improves the accuracy of the CI fuser. The proposed modified CI fuser will develop the EI fusion method in the sense that the conservative cross-covariances information is applied to determine the minimal upper bound of the actual variances of the original CI fuser, so that the robust accuracy of the original CI fuser is improved.

In addition, two robust weighted measurement fusion Kalman smoothers will be presented, which are equivalent to the robust centralized fusion Kalman smoother. The global optimal weighted fusers with exactly known model parameters and noise variances [6,8,13,34,35] are extended to the robust weighted fusers with uncertain noise variances.

The robustness of the proposed local and fused robust Kalman smoothers will be proved by the Lyapunov equation approach [24], which is completely different from the Riccati equation approach and the LMI approach [22]. Their robust accuracy relations are analyzed and proved. Specially, the corresponding robust local and fused steady-state Kalman smoothers will be presented for multisensor time-invariant system with uncertain noise variances, and under the weak condition that the measurement data are bounded [5], the convergence in a realization between the time-varying and steady-state Kalman smoothers will be proved rigorously by the dynamic error system analysis (DESA) method and the dynamic variance error system analysis (DVESA) method [5,30]. By the DESA method [5], the convergence problem of estimators is converted into the stability problem of a dynamic error system. By the DVESA method [30], the convergence problem of variances is converted into the stability problem of a Lyapunov equation.

The remainder of this paper is organized as follows: Section 2 gives the problem formulation. The local robust time-varying Kalman smoothers are presented in Section 3. The six weighted fusion robust time-varying Kalman smoothers together with