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Robust weighted state fusion Kalman estimators for networked systems with mixed uncertainties

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ABSTRACT

This paper is concerned with robust weighted state fusion estimation problem for a class of time-varying multisensor networked systems with mixed uncertainties including uncertain-variance multiplicative and linearly correlated additive white noises, and packet dropouts. By augmented state method and fictitious noise technique, the original system is converted into one with only uncertain noise variances. According to the minimax robust estimation principle, based on the worst-case system with the conservative upper bounds of uncertain noise variances, four weighted state fusion robust Kalman estimators (filter, predictor and smoother) are presented in a unified form that the robust filter and smoother are designed based on the robust Kalman predictor. Their robustness is proved by the Lyapunov equation approach in the sense that their actual estimation error variances are guaranteed to have the corresponding minimal upper bounds for all admissible uncertainties. Their accuracy relations are proved. The corresponding robust local and fused steady-state Kalman estimators are also presented, and the convergence in a realization between the time-varying and steady-state robust Kalman estimators is proved by the dynamic error system analysis (DESA) method. Finally, a simulation example applied to uninterruptible power system (UPS) shows the correctness and effectiveness of the proposed results.

1. Introduction

The aim of multisensor information fusion estimation is how to fuse the local measurements or local state estimators to obtain a fused state estimator, whose accuracy is higher than that of each local state estimator. Due to parallel structures, the distributed fusion method can significantly reduce the computation and communication burden. It is suitable for fault detection and isolation, and can give a global optimal or suboptimal fused estimator. Some distributed fusion filters have been presented in recent years. For example, for multisensor system with known noise variances, the optimal weighted measurement fusion Kalman estimators were presented in [1], and three global suboptimal weighted state fusion Kalman estimators weighted by matrices, diagonal matrices and scalars respectively were presented in [2–4] under the unbiased linear minimum variance (ULMV) rule. Also, by convex combination, the covariance intersection (CI) fused algorithm in [5–7] gives a common upper bound of actual estimation error variances, which is independent of unknown uncertain actual cross-variances. However, the classical Kalman filter requires the assumption that the model parameters and noise variances are precisely known. This assumption does not always hold in practical applications due to unmodeling dynamic and uncertain perturbations. This has motivated many studies on robust Kalman filtering in the past few years.

For linear discrete multisensor stochastic systems with uncertain noise variances, according to the minimax robust estimation principle [8], based on the worst-case conservative systems with the conservative upper bounds of uncertain noise variances, the robust local and fused Kalman filters [9], predictors [10], smoothers [11], and white noise deconvolution smoothers [12] have been presented, respectively. The actual estimation error variances or their traces of each estimator are guaranteed to have a minimal upper bound for all admissible actual noise variances. However, the common limitation of references [9–12] is that only the noise variance uncertainty is considered, while the model parameters of the considered system are all assumed to be known exactly, and the correlated noises are not considered.

For systems with the model parameter uncertainties, the algebraic Riccati equations approach [13] and linear matrix inequality (LMI) approach [14] were widely applied to design the robust Kalman filter. Its objective is to give a minimal upper bound of actual estimation error variances for all admissible uncertainties. Generally, multiplicative noises constitute an important class of stochastic parameters uncertainties. It has already received much attention in recently years,

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such as, target tracking system [15], synthetic aperture radar (SAR) systems [16], and image processing systems [17]. In addition, the linear quadratic regulation problem was addressed for discrete-time systems with multiplicative noises in [18], where the multiplicative noises only occur in the state matrix. The estimation problem under the case that the multiplicative noises only occur in the measurement matrix was considered in [19] based on projection theory. Further, under the case that the multiplicative noises occur both in the state and measurement matrices in [20–22], the authors addressed the robust Kalman filtering problem based on Riccati equations approach [20] and LMI approach [21], and innovation analysis approach [22].

However, the common limitation of references [13–22] is that only the stochastic parameter uncertainties have been considered, but the noise variance uncertainties have not been considered, i.e., the noise variances are assumed to be exactly known. Also the uncertain multiplicative noise variances are seldom considered [15]. Notice that it may be difficult to obtain the exact multiplicative noise variances for a practical system, and thus the problem of uncertain multiplicative noise variances has been addressed in [23,24]. The robust fusion Kalman estimators were considered for systems with multiplicative noises, linearly correlated noises, and uncertain noise variances in [25–28], but the multiplicative noises only occur in the state matrix [25], the same multiplicative noises occur in the state and measurement matrices [26,27]. The uncertain multiplicative noise variances were considered in [28]. However, the references [25–28] all do not consider the problem of packet dropouts.

In networked systems [29], the performance of estimation is strongly influenced by the limited capacity of the communication channels and sensor faults, such as packet outputs, random delay, and missing measurement are almost inevitable during data transmissions [30–33]. Therefore, it is not surprising that the robust estimation problem with packet dropout has attracted considerable attention in recent years. Generally, the popular approach for modeling this uncertainty is one with a Bernoulli binary sequence taking values 0 and 1 with known probabilities. In [30], the authors addressed the suboptimal and optimal distributed fusion estimation schemes for stochastic discrete-time linear systems with random packet loss. In [31], the authors studied the state fusion estimation problem for multi-sensor networked systems with packet dropouts. In [32], the authors designed a suboptimal filter for system with packet dropouts by solving a Riccati equation. In [33], the distributed fusion Kalman filtering problem was considered networked for systems with packet dropouts and random transmission delays.

The common limitation of references [30–33] is that only the packet dropouts has been considered, but the multiplicative noise uncertainties and uncertain noise variances have not been considered. In [34], the guaranteed cost robust weighted measurement fusion estimation problem has been considered for multisensor system with both uncertain noise variances and missing measurements by the Lyapunov equation approach, but the multiplicative noise uncertainties have not been considered.

In networked systems, stochastic parametric uncertainties and packets dropouts may exist simultaneously [35–40]. For example, in [35], the optimal linear estimation problem for linear discrete-time single sensor systems with multiplicative noise in state and measurement matrices and with packet dropouts was addressed based on the projection theory. The filtering problem for systems with multiplicative noise and different packet dropouts rates was addressed in [36], where a robust finite-horizon filtering minimizing the upper bound of the estimation error covariance was proposed. In [37], the authors discussed the fault estimation problem for a class of time-varying networked systems in the simultaneous presence of randomly occurring uncertainties, stochastic nonlinearities and packet dropouts. In [38], the robust Kalman filtering problem is investigated for uncertain stochastic systems with bounded random observation delays and missing measurements. Specially, in [39,40], by using the state augmentation approach, the authors investigated the filtering problem for networked systems, where multiplicative noises occur in both the state and measurement matrices, simultaneously with packet dropouts. The common limitation of references [35–40] is that the noise variance uncertainties have not been considered.

Notice that the filtering problems for systems with linear correlated noises often appear, where the measurement noise is linear function of process noise [25–28]. For example, the autoregressive moving average (ARMA) model can be converted into the state space model with linear correlated noises in signal processing. The noise may be auto-correlated or finite-step auto-correlated, if it is modeled as ARMA model or MA model. The robust filtering problems have been widely studied for systems with auto-correlated and/or cross-correlated noises [22,25–28,41,42].

Motivated by the above discussions, in this paper, the robust weighted fusion estimation problem for a class of time-varying multi-sensor systems with uncertain-variance multiplicative and linearly correlated additive white noises, and packet dropouts is addressed. The key idea and principle of the proposed design approaches for solving robust fused Kalman filtering problem, and the encountered essential difficulty are as following:

1. Applying the fictitious noise technique [25–28] to compensate the multiplicative noises, using the augmented state method, the system with multiplicative noises, packet dropouts and uncertain noise variances can be converted into one with only uncertain noise variances.
2. For system with only uncertain noise variances, applying minimax robust estimation principle [9–11], based on the worst-case conservative system with conservative upper bounds of noise variances, to design the minimum variance Kalman estimator will yields the robust Kalman estimator in the sense that its actual error variances have the minimal upper bounds for all admissible uncertain noise variances. This is called robustness. The proof of robustness for local and fused Kalman estimators becomes an essential difficult problem.
3. The robustness of robust Kalman estimators is proved by the proposed Lyapunov equation approach [9–11]. The problem is converted into one of the stability of a Lyapunov equation, i.e., whether its solution is positive-semi definite, if its input is positive-semi definite. While the positive-semi definiteness for a matrix can be proved by the proposed decomposition method.
4. A unified estimation approach [25–28] is used to design the robust Kalman estimators (filter, predictor and smoother), where the robust Kalman filter and smoother are designed based on the robust Kalman predictor.
5. By weighted state fusion approach, the local robust Kalman estimators are respectively weighted by matrices, scalars, diagonal matrices, CI matrices, we obtain the four robust weighted state fusers in a unified framework.
6. The convergence in a realization between time-varying and steady-state robust Kalman estimators were proved by the dynamic error system analysis (DESA) method [9,10].

The novelty of the topic of this paper is highlighted as follows:

The robust weighted state fusion Kalman filtering problem for networked systems with mixed uncertainties including three uncertainties: multiplicative noises in state and measurement matrices, uncertain multiplicative and additive noises variances, and packet dropouts, are simultaneously considered for the first time.

The major contributions and innovations of this paper are as follows:

For multisensor networked time-varying systems with mixed uncertainties including uncertain-variance multiplicative and linearly correlated additive white noises, and packet dropouts, applying fictitious noise technique, augmented state method, minimax robust estimation principle, and unified estimation approach, four weighted state