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Multi-sensor information fusion estimators for stochastic uncertain systems with correlated noises

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ABSTRACT

The information fusion estimation problems are investigated for multi-sensor stochastic uncertain systems with correlated noises. The stochastic uncertainties caused by correlated multiplicative noises exist in the state and observation matrices. The process noise and the observation noises are one-step auto-correlated and two-step cross-correlated, respectively. While the observation noises of different sensors are one-step cross-correlated. The optimal centralized fusion filter, predictor and smoother are proposed in the linear minimum variance sense via an innovative analysis approach. To enhance the robustness and flexibility, a distributed fusion filter is put forward, which requires the calculation of filtering error cross-covariance matrices between any two local filters. To avoid the calculation of cross-covariance matrices, another distributed fusion filter is also presented by using the covariance intersection (CI) fusion algorithm, which can reduce the computational cost. A simulation example is given to show the effectiveness of the proposed algorithms.

1. Introduction

In recent years, the research on networked control systems and sensor networks has attracted much attention due to their wide applications [1–5]. In networked control systems, random delays and missing measurements are unavoidable due to the limited communication capability. This kind of systems can be transformed into stochastic uncertain parameterized systems with multiplicative noises. Recent results on the estimation problems with random time delays and packet dropouts during data transmission have been reported [6–9].

In fact, with the expanding of the scale and complexity of control systems, in addition to the uncertainty of transmission delays and losses induced by networks, various external immeasurable disturbances widely exist. One of them is stochastic multiplicative noise which makes the system nonlinear. This makes it harder to design an estimator and controller. They widely exist in the engineering applications. For example, the parameter uncertainties of the systems can be described by multiplicative noises. The systems with missing measurements, quantization effects and randomly occurring sensor saturations can be converted into the model with multiplicative noises [10,11]. Nonlinear polynomial filters are presented for systems with multiplicative noises [12]. However, it is not suitable for real-time applications since the algorithm has an expensive computational cost. To reduce the computational burden, linear optimal estimators are designed based on an innovation analysis approach [13].

In most filtering algorithms, it is usually assumed that the observation noises of different sensors are uncorrelated. However, in the engineering applications, a lot of practical systems involve the correlated noises. For example, correlated noises exist in systems which observe a dynamic process in a common noisy environment. The correlated noises will be brought by discretizing a continuous-time system or transforming a descriptor system into a normal one [14]. Some estimation algorithms for this kind of systems have been presented in the recent works [15–28]. The filtering algorithms are designed for nonlinear systems with correlated noises in [15–17] where the process and measurement noises are only correlated at the same time. The Kalman-type filters have been designed for systems with finite-step auto-correlated noises [18,19]. A recursive Kalman-type filter has been also designed for descriptor systems with one-step auto-correlated observation noises and packet dropouts [20]. However, the filters in [18–20] are suboptimal since they are fixed as the Kalman-type forms. Recently, the optimal filter is designed for a class of uncertain dynamical systems with finite-step correlated noises and packet dropouts [21]. However, the aforementioned literatures are confined to the single-sensor systems. Multiple sensors are not taken into account.

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With the development of science and technology, in order to meet the higher accuracy requirements, the information fusion filters for multi-sensor systems have been widely applied. The traditional methods include the centralized and distributed fusion filtering algorithms. As everyone knows, the former has the best accuracy when all sensors work healthily. Its main drawbacks are the bad robustness and flexibility. The latter can overcome those shortcomings and maintain higher accuracy than local estimators. Recently, [22] investigates the optimal filtering problem for a class of discrete-time stochastic systems with random parameter matrices and correlated additive noises. The multiplicative noises between state and observation matrices are uncorrelated. Moreover, a centralized fusion filter is given to treat the networked systems with the one-step delays and missing measurements. However, the centralized fusion multi-step predictor and smoother are not investigated. Moreover, the distributed fusion filter is not also studied, which has better robustness and flexibility than the centralized fusion filter. A Kalman-type centralized fusion filter has been designed in [23] for a nonlinear system with random parameter matrices, multiple fading measurements and correlated noises. For multi-sensor systems with cross-correlated observation noises, the distributed Kalman filtering fusion problem is investigates in [24] where both with and without feedback from the fusion center to local sensors are discussed. For uncertain systems with auto- and cross-correlated noises, the suboptimal Kalman-type local filter and distributed fusion filter are designed [25] by using the matrix-weighted fusion estimation algorithm in [26]. For multi-sensor systems with the cross-correlated noises, the sequential and distributed fusion filtering problems are studied in [27]. Recently, the centralized and distributed fusion filters are also designed for multi-sensor systems with missing measurements and correlated noises in [28]. However, the stochastic uncertainties of systems are not taken into account in [27,28].

In aforementioned literatures [25–28], the proposed distributed fusion filters require the computation of cross-covariance matrices between any two local filters. However, sometimes the calculation of cross-covariance matrices may be complex and difficult; even be impossible in many practical applications. Then the distributed fusion algorithms in [25–28] are no longer applicable. To overcome the limitations, the covariance intersection (CI) fusion method is presented in [29–31]. The CI fusion method avoids the calculation of cross-covariance matrices between any two local estimators and can obtain higher accuracy than any local filters.

Motivated by the above considerations, this paper is written to solve the information fusion estimation problems for multi-sensor stochastic uncertain systems with auto- and cross-correlated noises. The stochastic uncertainties of correlated multiplicative noises exist in state and observation matrices. Firstly, a centralized fusion filter is presented via an innovation analysis approach. Based on it, the centralized fusion multi-step predictor and smoother are also presented. It is well known that centralized fusion filter has bad robustness and flexibility though it can obtain the best filtering accuracy when all sensors work healthily. Then, a distributed fusion filter with the robustness and flexibility is presented by using matrix-weighted fusion estimation algorithm in the linear minimum variance sense [26]. Filtering error cross-covariance matrices between any two local filters are derived. To reduce the computational cost, another distributed fusion filter that avoids the calculation of cross-covariance matrices is also given by using the CI fusion algorithm [29–31]. It has worse accuracy than the distributed fusion filter weighted by matrices but better accuracy than any local filter.

The rest is organized as follows: In Section 2, the studied problem is formulated. In Section 3, the centralized fusion filter, predictor and smoother are designed. In Section 4, the distributed matrix-weighted fusion filter and distributed CI fusion filter are presented. In Section 5, a simulation example is given. The last part of this paper is the conclusion. Appendices A–D provide the mathematical details.

Nations: superscript T denotes the transpose; E denotes the mathematical expectation; tr denotes the trace of a matrix; δ_{tk} is the Kronecker delta function; I_{p_i} is a p_i by p_i identity matrix; $1_{p_ip_j}$ is a p_i by p_j matrix of all ones; $\odot$ is the Hadamard product; $\perp$ denotes orthogonality. diag$(\cdot)$ is the diagonal matrix whose diagonal elements consist of "$\cdot$"; Superscript $(i),(o),(c)$ and (CI) means the ith sensor, distributed weighted fusion, centralized optimal fusion and covariance intersection (CI) fusion, respectively. $\hat{x}(\circ|\bullet)$ denotes the estimate of stochastic variable $x(\circ)$ based on information $\bullet$, i.e., the projection of $x(\circ)$ on the linear space generated by information $\bullet$. $\tilde{x}(\circ|\bullet)=x(\circ)-\hat{x}(\circ|\bullet)$ denotes the estimation error. $P_{xy}^{(ab)}(\circ|\bullet)$ is the covariance matrix between estimation errors $\tilde{x}^{(a)}(\circ|\bullet)$ and $\tilde{y}^{(b)}(\circ|\bullet)$, with $P_{xy}^{(aa)}(\circ|\bullet)=P_{xy}^{(a)}(\circ|\bullet)$ and $P_{xx}^{(ab)}(\circ|\bullet)=P_{x}^{(ab)}(\circ|\bullet)$.

2. Problem formulation

Consider the following stochastic uncertain system with multiple sensors:

$$x(t+1)=(\Phi(t)+\zeta(t)F(t))x(t)+\Gamma(t)w(t) \tag{1}$$

$$y^{(i)}(t)=(H^{(i)}(t)+\xi^{(i)}(t)C^{(i)}(t))x(t)+v^{(i)}(t),i=1,2,\ldots,L \tag{2}$$

where $x(t)\in R^n$ is the system state to be estimated. $y^{(i)}(t)\in R^{p_i}$, $i=1,2,\ldots,L$ is the observation of the ith sensor, L is the number of sensors. $\zeta(t)\in R$ and $\xi^{(i)}(t)\in R, i=1,\ldots,L$ are scalar multiplicative noises. $w(t)\in R^m$ and $v^{(i)}(t)\in R^{p_i}$ are the process noise and observation noise of the ith sensor. $\Phi(t),F(t),\Gamma(t),H^{(i)}(t)$ and $C^{(i)}(t)$ are known time-varying matrices with suitable dimensions.

Assumption 1. $\zeta(t)$ and $\xi^{(i)}(t),i=1,\ldots,L$ are correlated white noises satisfying

$$E[\zeta(t)]=0,E[\xi^{(i)}(t)]=0;\ E[\zeta(t)\zeta^T(k)]=Q_\zeta(t)\delta_{t,k};$$
$$E[\xi^{(i)}(t)\xi^{(j)T}(k)]=Q_\xi^{(ij)}(t)\delta_{t,k};\ E[\zeta(t)\xi^{(i)T}(k)]=Q_{\zeta\xi}^{(i)}(t)\delta_{t,k} \tag{3}$$

where $Q_\xi^{(ii)}(t)=Q_\xi^{(i)}(t)$.

It is clear from (3) that state multiplicative noise $\zeta(t)$ and observation multiplicative noises $\xi^{(i)}(t),i=1,\ldots,L$ are correlated with each other at the same moment, which can be found in networked systems [4,6,32] where the networked systems with random delays and packet losses are transformed into those with correlated multiplicative noises in the state and measurement matrices.

Assumption 2. $w(t)$ and $v^{(i)}(t)$ are correlated white noises satisfying

$$E[w(t)]=0;E[v^{(i)}(t)]=0;\ E[w(t)w^T(k)]=Q(t,k)(\delta_{t,k}+\delta_{t,k-1}+\delta_{t,k+1})$$
$$E[v^{(i)}(t)v^{(j)T}(k)]=R^{(ij)}(t,k)(\delta_{t,k}+\delta_{t,k-1}+\delta_{t,k+1});\ E[w(t)v^{(i)T}(k)]$$
$$=S^{(i)}(t,k)(\delta_{t,k}+\delta_{t,k-1}+\delta_{t,k-2}) \tag{4}$$

where $R^{(ii)}(t,k)=R^{(i)}(t,k)$. $w(t)$ and $v^{(i)}(t),i=1,2,\ldots,L$ are independent of $\zeta(t)$ and $\xi^{(j)}(t),j=1,2,\ldots,L$.

We can draw the conclusion from (4) that the process noise and the observation noises are one-step auto-correlated, respectively. The observation noises of different sensors are one-step cross-correlated. Process noise and observation noises are two-step forward cross-correlated.