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Multi-sensor distributed fusion filtering for networked systems with different delay and loss rates

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ABSTRACT

This paper mainly focuses on the multi-sensor distributed fusion estimation problem for networked systems with time delays and packet losses. Measurements of individual sensors are transmitted to local processors over different communication channels with different random delay and packet loss rates. Several groups of Bernoulli distributed random variables are employed to depict the phenomena of different time delays and packet losses. Based on received measurements of individual sensors, local processors produce local estimates that have been developed in a new recent literature. Then local estimates are transmitted to the fusion center over a perfect connection, where a distributed fusion filter is obtained by using the well-known matrix-weighted fusion estimation algorithm in the linear minimum variance sense. The filtering error cross-covariance matrices between any two local filters are derived. The steady-state property of the proposed distributed fusion filter is analyzed. A simulation example verifies the effectiveness of the algorithm.

1. Introduction

During the past decades, the research on networked systems and sensor networks has attracted much attention since they make resources convenient for sharing and have broad applications including target tracking, signal processing, multiple robots, and so on [1–3]. The random delays and packet losses are usually induced by the network congestions during data transmissions of networked systems [4]. Therefore, the design on estimators and controllers for networked systems is challenging [5,6].

Several literatures have focused on single sensor systems with packets losses or/and time delays [7–14]. However, the research on multi-sensor systems subject to time delays and losses are not fully reported in the literatures. Multi-sensor information fusion has broad applications in target tracking, navigation and detection since they can fully make use of information from all sensors and overcome the defect of single sensor lying in the limitation of time and space. Thus, the study on multi-sensor information fusion is significant. Distributed fusion estimation plays an important role in information processing for multi-sensor systems. In [15], distributed consensus filters are designed for sensor networks, where each sensor implements the estimate based on the data from neighboring sensors. However, the communication time delays are not taken into account. Since the distributed fusion has better robust and flexibility than the centralized fusion, many results on the distributed fusion estimation have been reported in recent years, including the decentralized filter with the parallel structure [16], the federal Kalman filter [17], the Maximum Likelihood fusion filter [18], the unified optimal linear estimation fusion [19] and distributed fusion weighted by matrices [20]. Several fusion estimation algorithms have been designed for multi-sensor systems with the transmission delays or packet losses in [21–24], where, however, the delays and packet losses are not taken into account simultaneously. In [25–27], distributed and centralized fusion estimators have been respectively designed for packet losses and one-step random delays or variable delays. However, multi-step random delays are not taken into account. Distributed track-to-track fusion on Kalman-type filtering and retrodiction at arbitrary communication rates is also addressed for target tracking in [28,29], where the correlation among local filters is ignored.

Recently, a new model to depict the phenomena of multi-step random delays and packet losses during data transmissions in networked systems has been developed and an optimal linear filter has been presented in [30]. In this paper, we will generalize the results for single sensor in [30] to the case of multiple sensors. We will investigate the distributed fusion filtering problem as shown in Fig. 1. Each sensor transmits its measurements to a local processor over imperfect networks which lead to random delays and packet losses. Each local processor produces local estimate based on received measurements from sensor itself and then transmits

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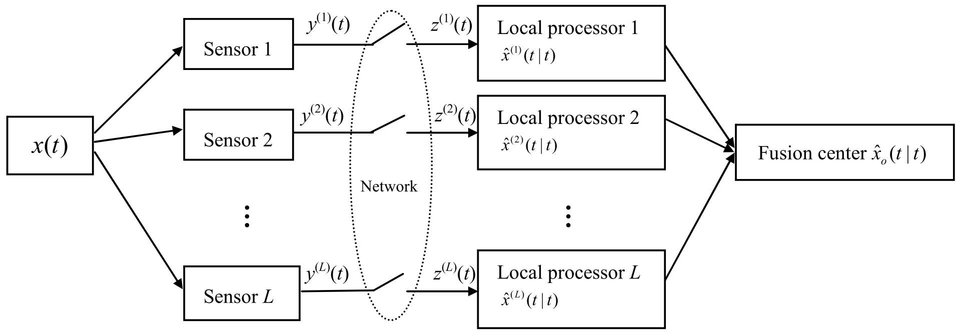

Fig. 1. Distributed fusion estimation scheme.

it to the fusion center over perfect connections without delays and losses. In the fusion center, all local filters are weighted by linear combination to give the fusion state filter. Several groups of Bernoulli distributed random variables with known probabilities are introduced to depict different transmission delay and loss rates from different sensors to local processors. The filtering error cross-covariance matrices between any two local filters are derived, which can be recursively computed with any initial values. Based on the local filters in [30] and the derived filtering error cross-covariance matrices, a distributed fusion filter weighted by matrices is obtained by using the linear minimum variance fusion algorithm [20]. At last, we analyze the steady-state property of the proposed distributed fusion filter. A sufficient condition for the existence of the steady-state fusion filter is given.

The rest of this paper is organized as follows. In Section 2, the system model and problem formulation are addressed. In Section 3, the local optimal linear filter is given. In Section 4, the cross-covariance matrices between any two local filters are derived. In Section 5, the stability and steady-state property are analyzed. Section 6 provides an example. Section 7 draws a conclusion.

2. Problem formulation

Consider the following discrete time-invariant linear systems with multiple sensors:

$$x(t+1) = Fx(t) + Dw(t) \tag{1}$$

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

where $x(t) \in R^n$ is the state, $y^{(i)}(t) \in R^{m_i}$ is the measured output of the ith sensor which will be transmitted to a local processor by networks, $w(t) \in R^r$ and $v^{(i)}(t) \in R^{m_i}$ are the process and measurement noises, respectively. L is the number of sensors, and F, D and $C^{(i)}$ are constant matrices with suitable dimensions.

The estimation problem considered is shown in Fig. 1. Suppose that packet losses and random delays exist in data transmissions from individual sensors to local processors. At every time, the packet of each sensor is only sent once in order to avoid the network congestion and only one packet or no packet is available at local processors. The packets received by the ith local processor can be described by the following mathematical model [30]:

$$\begin{aligned} z^{(i)}(t) = {} & \alpha_0^{(i)}(t)y^{(i)}(t) + \big(1-\alpha_0^{(i)}(t)\big)\Big\{\big(1-\alpha_0^{(i)}(t-1)\big)\alpha_1^{(i)}(t) \\ & \times y^{(i)}(t-1) + \big[1-\big(1-\alpha_0^{(i)}(t-1)\big)\alpha_1^{(i)}(t)\big] \\ & \times \Big\{\big(1-\alpha_0^{(i)}(t-2)\big)\big(1-\alpha_1^{(i)}(t-1)\big)\alpha_2^{(i)}(t)y^{(i)}(t-2) \\ & + \cdots + \Big[1-\prod_{k=0}^{d_i-2}\big(1-\alpha_k^{(i)}(t-d_i+k+1)\big)\alpha_{d_i-1}^{(i)}(t)\Big] \\ & \times \prod_{k=0}^{d_i-1}\big(1-\alpha_k^{(i)}(t-d_i+k)\big)\alpha_{d_i}^{(i)}(t)y^{(i)}(t-d_i)\Big\}\cdots\Big\} \end{aligned} \tag{3}$$

where $\alpha_k^{(i)}(t)$, $k = 0, 1, \cdots, d_i$; $i = 1, 2, \cdots, L$ are mutually uncorrelated Bernoulli distributed random variables with the probabilities $\mathrm{P}\{\alpha_k^{(i)}(t) = 1\} = \bar{\alpha}_k^{(i)}$ and $\mathrm{P}\{\alpha_k^{(i)}(t) = 0\} = 1 - \bar{\alpha}_k^{(i)}$, $\bar{\alpha}_k^{(i)} \in [0, 1]$. They are uncorrelated with other random variables.

The model (3) describes the phenomena of possible random d_i-step ($i = 1, \cdots, L$) delays and packet losses during data transmissions from individual sensors to local processors over the network. In order to explain the model, taking $d_i = 1$ as an example, then model (3) can be reduced to $z^{(i)}(t) = \alpha_0^{(i)}(t)y^{(i)}(t) + (1 - \alpha_0^{(i)}(t))(1 - \alpha_0^{(i)}(t-1))\alpha_1^{(i)}(t)y^{(i)}(t-1)$. It follows that $z^{(i)}(t) = y^{(i)}(t)$ if $\alpha_0^{(i)}(t) = 1$, (i.e., received on time); $z^{(i)}(t) = y^{(i)}(t-1)$ if $\alpha_0^{(i)}(t) = 0$, $\alpha_0^{(i)}(t-1) = 0$ and $\alpha_1^{(i)}(t) = 1$, (i.e., one-step delay); and $z^{(i)}(t) = 0$ if $\alpha_0^{(i)}(t) = 0$, $\alpha_0^{(i)}(t-1) = 1$ or $\alpha_0^{(i)}(t) = 0$, $\alpha_1^{(i)}(t) = 0$, (i.e., packet loss).

In this paper, 0 and I denote the zero and identity matrices of suitable dimensions, respectively. Our work is done based on the following assumptions.

Assumption 1. $w(t)$ and $v^{(i)}(t)$ are correlated white noises with zero mean and variances Q_w, $Q_v^{(i)} = Q_v^{(ii)}$, and cross-covariance matrices $S^{(i)}$ and $Q_v^{(ij)}$, $i \neq j$, i.e.,

$$\mathrm{E}\left\{\begin{bmatrix} w(t_1) \\ v^{(i)}(t_1)\end{bmatrix}\begin{bmatrix} w^{\mathrm{T}}(t_2) & v^{(j)\mathrm{T}}(t_2)\end{bmatrix}\right\} = \begin{bmatrix} Q_w & S^{(j)} \\ S^{(i)\mathrm{T}} & Q_v^{(ij)}\end{bmatrix}\delta_{t_1t_2} \tag{4}$$

where E is the mathematical expectation, T is the transpose operator, and $\delta_{t_1t_2}$ is the Kronecker delta function.

Assumption 2. The initial state $x(0)$ is uncorrelated with $w(t)$ and $v^{(i)}(t)$ and satisfies

$$\mathrm{E}\big[x(0)\big] = \mu_0, \qquad \mathrm{E}\big[\big(x(0)-\mu_0\big)\big(x(0)-\mu_0\big)^{\mathrm{T}}\big] = P_0 \tag{5}$$

Our objective is to design the distributed fusion filter weighted by matrices in the linear minimum variance sense by the linear combination of the local linear filters from local processors. We first give local linear filters based on the measurement data of individual sensors, then compute the filtering error covariance matrices including auto- and cross-covariance matrices, at last obtain the distributed fusion filter.

Remark 1. According to the definition of $\alpha_k^{(i)}(t)$, we have the following results: $\mathrm{E}[\alpha_k^{(i)}(t)] = \bar{\alpha}_k^{(i)}$, $\mathrm{E}[(\alpha_k^{(i)}(t) - \bar{\alpha}_k^{(i)})^2] = \bar{\alpha}_k^{(i)}(1 - \bar{\alpha}_k^{(i)})$, $\mathrm{E}[\alpha_k^{(i)}(t)(1 - \alpha_k^{(i)}(t))] = 0$, $\mathrm{E}[\alpha_p^{(i)}(l)\alpha_k^{(i)}(t)] = \bar{\alpha}_p^{(i)}\bar{\alpha}_k^{(i)}$, $l \neq t$ or $p \neq k$, $\mathrm{E}[\alpha_p^{(i)}(l)\alpha_k^{(j)}(t)] = \bar{\alpha}_p^{(i)}\bar{\alpha}_k^{(j)}$, $i \neq j$; $i, j = 1, \cdots, L$; $k, p = 0, \cdots, d_i$.