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Brief paper

Sequential fusion estimation for clustered sensor networks[☆]

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ABSTRACT

We consider multi-sensor fusion estimation for clustered sensor networks. Both sequential measurement fusion and state fusion estimation methods are presented. It is shown that the proposed sequential fusion estimation methods achieve the same performance as the batch fusion one, but are more convenient to deal with asynchronous or delayed data since they are able to handle the data that are available sequentially. Moreover, the sequential measurement fusion method has lower computational complexity than the conventional sequential Kalman estimation and the measurement augmentation methods, while the sequential state fusion method is shown to have lower computational complexity than the batch state fusion one. Simulations of a target tracking system are presented to demonstrate the effectiveness of the proposed results.

1. Introduction

Fusion estimation for sensor networks has attracted much research interest during the last decade, and has found applications in a variety of areas (Cao et al., 2014; Chen, Li, & Lai, 2013; He, Wang, Ji, & Zhou, 2011; Ilic, Xie, Khan, & Moura, 2010; Oka & Lampe, 2010). Compared with the centralized structure, the distributed structure is more preferable for sensor networks because of its reliability, robustness and low requirement on network bandwidth (Dong, Wang, & Gao, 2012; Duan & Li, 2011; He et al., 2011; Millan et al., 2013; Yan, Xiao, Xia, & Fu, 2013). When the number of sensors is large, it is wasteful to embed in each sensor an estimator and the communication burden is high. Moreover, for long-distance deployed sensors, it may not be possible to allocate communication channels for all sensors. An improvement is to adopt the hierarchical structure for distributed estimation (Song, Zhang, & Yu, 2014; Zhang, Qi, & Deng, 2014), by which all the sensors in the network are divided into several clusters and the sensors within the same cluster are connected to a cluster head (CH) which acts as a local estimator. Then, the distributed estimation is carried out in two stages. In the first stage, the local estimator in each cluster fuses the measurements from its cluster to generate a local estimate. Then, the local estimators exchange and fuse local estimates to produce a fused estimate to eliminate any disagreements among themselves.

Various results on multi-sensor fusion estimation for sensor networks have been available in the literature, including centralized fusion and distributed fusion, as well as measurement fusion and state fusion (Bar-Shalom & Li, 1995; Deng, 2006; Hu, Duan, & Zhou, 2010; Julier & Uhlman, 2009; Ran & Deng, 2009; Roecker & McGillem, 1988; Song, Zhu, Zhou, & You, 2007; Sun & Deng, 2004; Xia, Shang, Chen, & Liu, 2009; Xing & Xia, 2016; Zhang, Chen Michael, Liu, & Liu, 2017; Zhang, Liu, & Yu, 2014). However, most of the results are based on the idea of batch fusion, that is, measurements or local estimates are fused all at a time at the fusion instant until all of them are available at the estimator, as illustrated in Fig. 1(a). Such a batch fusion estimation may induce long computation delay, thus it is not appropriate for real-time applications. A possible improvement is to adopt the idea of sequential fusion (Aran, Burger, Caplier, & Akarun, 2009; Shen, Luo, Zhu, & Song, 2012), by which the measurements or local estimates are fused one by one according to the time order of the data arriving at the estimator, as illustrated in Fig. 1(b). In this way, the fusion and the state estimation could be carried out over the entire estimation interval, which help reduce computation burdens at the estimation instant and ultimately reduce the computation delay. Some relevant results on sequential fusion estimation have been presented in Deng, Zhang, Qi, Liu, and Gao (2012), Huang and Qin (2010) and Yan, Li, Xia, and Fu (2013, 2015). The results in Yan, Li et al. (2013) and Yan et al. (2015) provide an efficient measurement fusion estimation approach to deal with asynchronous or delayed

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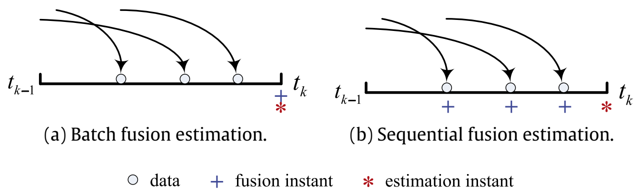

Fig. 1. Examples of batch fusion estimation and sequential fusion estimation.

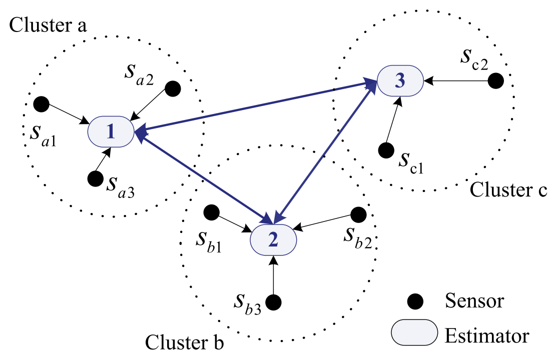

Fig. 2. A structure of hierarchical fusion estimation for clustered sensor networks.

data, and the idea is similar to the conventional sequential Kalman filtering, where the state estimate is updated several times by sequentially fusing the various measurements generated at different time instants, and both the procedures of state prediction and measurement updating are involved over each step of the estimate updating. An alternative approach is to fuse all the measurements first, and then generate the state estimate based on the fused measurement. This is the novel method introduced in this paper. In Deng et al. (2012), the sequential covariance intersection (CI) fusion method was presented for state fusion estimation. However, the CI fusion is not optimal since the cross-covariances among the various local estimates are ignored. An improved sequential state fusion estimation method was presented in Huang and Qin (2010) by taking the cross-covariances among the local estimates into consideration and using the matrix weights approach.

In this paper, both sequential measurement fusion (SMF) estimation and state fusion estimation (SSF) methods are developed for clustered sensor networks, where the SMF is presented for local estimation, while the SSF is presented for state fusion estimation among all the local estimators. The main contributions of the paper are summarized as follows:

(1) We present a design method for the SMF estimators. We show that the SMF estimator is equivalent to the conventional sequential Kalman (SK) and the batch measurement fusion (BMF) estimators, and is equivalent to the one designed based on measurement augmentation (MA). We also show that the SMF estimator has lower computational complexity than the estimators based on SK and MA.

(2) We present a design method for the SSF estimators with matrix weights. We further show that the SSF estimator is equivalent to the batch state fusion (BSF) estimators with matrix weights but has much lower computational complexity.

Notation: For a random variable $x \in \Re^n$, we denote its mean by $\mathbf{E}\{x\}$ and its covariance by $\mathrm{Var}\{x\}$. $x \perp y$ denotes orthogonal vectors x and y, $\hat{x}$ and $\tilde{x}$, respectively, denote the estimate and estimation error of the state x. $P(k) = P(k|k) = \mathrm{Var}\{\tilde{x}(k)\}$ represents the estimation error covariance, $\mathrm{tr}(A)$ denotes the trace of the matrix A, and $\mathrm{diag}\{\cdot\}$ stands for a block-diagonal matrix.

2. Problem statement

Consider the hierarchical fusion estimation for clustered sensor networks as shown in Fig. 2, where the plant, whose state is to be estimated, is described by the following discrete-time state-space model:

$$x(k+1) = A(k)x(k) + B(k)\omega(k) \tag{1}$$

where $x(k) \in \Re^{n_x}$ is the system state, and $\omega(k) \in \Re^{n_\omega}$ is a zero-mean white Gaussian noise with variance Q_ω. A sensor network with m clusters is deployed to monitor the state of system (1). The set of the clusters is denoted by $\Phi = \{1, \ldots, m\}$. Let $\mathcal{N}_s = \{1, \ldots, n_s\}$ denote the sth cluster in the sensor network, where $s \in \Phi$ and n_s is the number of sensors in the cluster $\mathcal{N}_s$. The n_s sensors are connected to a cluster head (CH) e_s serving as an estimator. The measurement equation of each sensor is given by

$$y_{s,i}(k) = C(k)x(k) + \upsilon_{s,i}(k),\ i \in \mathcal{N}_s,\ s \in \Phi \tag{2}$$

where $y_{s,i}(k) \in \Re^q$, $\upsilon_{s,i}(k)$ is a zero-mean white Gaussian noise with variance $R_{s,i}$, and $\upsilon_{s,i}(k)$ are mutually uncorrelated and are uncorrelated with $\omega(k)$.

As shown in Fig. 2, the fusion estimation is carried out in two stages. At the first stage, each CH collects and fuses measurements sequentially from its cluster, then generates a local estimate using the fused measurement. At the second stage, each CH collects local estimates from itself and the other CHs to produce a fused state estimate using the SSF method to improve estimation performance and eliminate any disagreements among the estimators.

3. Design of the SMF estimators

This section is devoted to the design of the SMF estimators for each cluster. Consider cluster $\mathcal{N}_s$, $s \in \Phi$. For notational convenience, the subscript s in the notations will be dropped in the remaining of this section, for example, $y_{s,i}(k)$ is denoted as $y_i(k)$ and n_s is denoted as n. Denote $y_f^s(k)$ as the fused measurement and $Y(k) = \{y_1(k), \ldots, y_n(k)\}$ as the set of measurements for fusion. Then it can be seen from Fig. 1(b) that $y_f^s(k)$ is obtained by sequentially fusing the n measurements. The fused measurement and its noise variance of the jth fusion over the interval $(k-1, k]$ are denoted by $y_{(j)}(k)$ and $R_{(j)}(k)$, respectively, where $j \in \{1, 2, \ldots, n-1\}$. Denote the measurement noise of $y_{(j)}(k)$ as $\upsilon_{(j)}(k)$, then $y_{(j)}(k) = C(k)x(k) + \upsilon_{(j)}(k)$, and $R_{(j)}(k) = \mathrm{Var}\{\upsilon_{(j)}(k)\}$. In the remainder of this section, unless stated otherwise, the time index k will be dropped for notational convenience. We now introduce the first main result on SMF estimator.

Theorem 1. *For the measurements in $Y(k)$, the SMF estimator is given by the following equations:*

$$R_{(j)} = \left[R_{(j-1)}^{-1} + R_{j+1}^{-1}\right]^{-1} \tag{3}$$

$$y_{(j)} = R_{(j)}\left[R_{(j-1)}^{-1} y_{(j-1)} + R_{j+1}^{-1} y_{j+1}\right] \tag{4}$$

where $j = 1, \ldots, n-1$, $y_{(0)} = y_1$, $R_{(0)} = R_1$, and the fused measurement y_f^s and its noise variance R_f^s are given by $y_f^s = y_{(n-1)}$ and $R_f^s = R_{(n-1)}$, respectively. Moreover, one has $R_{(j)} \leq R_{(j-1)}$ and $R_f^s(k) \leq R_i$, $i \in \{1, \ldots, n\}$.

Proof. Denote f_m as the sequential measurement fusion operator, then $y_{(j)} = f_m\{y_{(j-1)}, y_{j+1}\}$. Augment $y_{(j-1)}$ and y_{j+1} to get

$$z_{(j)} = \begin{bmatrix} y_{(j-1)} \\ y_{j+1} \end{bmatrix} = eCx + \bar{\upsilon}_{(j)} \tag{5}$$

where $e = [I \quad I]^{\mathrm{T}}$ and $\bar{\upsilon}_{(j)} = [\upsilon_{(j-1)}^{\mathrm{T}} \quad \upsilon_{j+1}^{\mathrm{T}}]^{\mathrm{T}}$. Let $\bar{R}_{(j)} = \mathrm{Var}\{\bar{\upsilon}_{(j)}\}$. The term $z_{(j)}$ can be regarded as a measurement of Cx with the