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Sequential Fusion for Asynchronous Multi-sensor Fading Measurements

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Abstract

In this paper, the fusion filtering problem has been investigated for multi-sensor time varying systems with fading measurements, the probabilistic fading phenomenon of which is described by statistical means and variances. A real-time unbiased fusion filtering algorithm has been proposed in the sequential fusion frame. The asynchronous fading measurements are firstly transformed into pseudo fading measurements of the fusion state in the current fusion interval. A novel noise estimation method is presented to deal with the correlations during pseudo measurement noises, which is strictly deduced in the sense of Linear minimum-mean-square error (LMMSE). On this basis, these fading measurements are handled sequentially in their arriving sequence without matrix augmenting. The finial computer simulation demonstrates the effectiveness of the proposed sequential fusion filtering method.

Keywords*: Fading measurement, asynchronous multi-sensor system, sequential fusion filtering, noise estimation*

1. Introduction

In many real world applications, multiple homogeneous or heterogeneous sensors are spatially distributed to provide a large coverage, diverse viewing angles of the things of interest. Various measurements for the same object are sampled by different sensors. How to deal with these measurements to achieve refined state estimation of the multi-sensor system? A smart and effective method is the data fusion technology, which has received considerable attention due to its extensive application domains such as target tracking, power system and intellective traffic.

In the past few decades, a rich body of literature has appeared on the data fusion method. For all sensors work with the same sampling rate at the same time, several effective synchronous fusion methods are presented [1-3]. In practice, however, synchronizing all the sensors is often difficult, and thus the measurements are usually sampled asynchronously [4]. The fusion problem of asynchronous multi-sensor systems has received constant attention and a series of results have been published [5-10]. By transform the asynchronous fusion problem to the pseudo synchronous fusion problem, a suboptimal asynchronous track fusion method is given in [5]. For the linear time-invariant systems with energy bounded noises, a asynchronous $H\infty$ fusion filter design method is proposed in [6]. Subsequently, several centralized fusion filtering method is presented for the multi-rate sensor systems [7] or asynchronous nonlinear systems [8, 9]. In order to improve the real time property, a recursive asynchronous fusion estimator is proposed in the sequential fusion frame [10], in which, however, the augmented matrix module requires a strong high-dimension matrix computing capabilities.

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In sensor network systems, fading measurements are now well known to be one of the most frequently occurred phenomena [11]. The measurements translated through communication networks could be subject to fading effects in power or amplitude, which are usually inevitable in the wireless network channels [12]. In this text, the measurement sampled by sensor is no longer equivalent to the input of the filter [13]. On this basis, a fading channel model has been developed by using the stochastic variables with nonzero mathematical expectations. Such a model can describe the fading measurements such as Rice fading channel [14]. The asymptotic stability of minimum mean-square error linear filter for single sensor fading measurement is analyzed in [15]. The single sensor fading measurement filtering problems are investigated for the discrete-time Takagi-Sugeno fuzzy systems [16], the systems with energy bounded noises[17], the random parameter systems [18, 19], and the fault detection process [13]. For multi-sensor fading measurements sampled synchronizationly, a centralized fusion Kalman filter is reported in [20]. However, to the best of the authors' knowledge, the fusion filtering problem has not been fully investigated for asynchronous multi-sensor fading measurements. It is, therefore, our aim in this paper to make a major effort to address the sequential asynchronous fusion filtering problem for multi-sensor fading measurements.

In this paper, we aim to investigate the real-time fusion filtering problem for asynchronous multi-sensor fading measurements in sequential fusion frame. Compared with the centralized fusion methods, the sequential fusion method has potential better real time property and lower high-dimension matrix computing requirement. The considered probabilistic fading phenomenon are described by statistical means and variances. Firstly, the asynchronous fading measurements are transformed into pseudo synchronous fading measurements. Then, these fading measurements are handled sequentially in their arriving sequence without matrix augmenting, by utilizing a novel noise estimation skill to deal with the correlations during pseudo measurement noises. The main contributions of this paper can be highlighted as follows: (1) the real-time sequential fusion filtering problem is investigated for the fading measurements sampled asynchronously by multi-sensor systems; (2) the presented fusion filter scheme is unbiased and optimal, which is strictly deduced in the sense of Linear minimum-mean-square error (LMMSE).

The remainder of this paper is organized as follows. In Section 2, the asynchronous fusion filtering problem is briefly formulated. A novel sequential fusion filtering algorithm for is presented in Section 3. In Section 4, simulations illustrate the viability and the effectiveness of the proposed algorithm. Finally, the conclusions are drawn in Section 5.

2. Problem Formulation

Consider the following multi-sensor time-varying system

$$x(k)=\Phi(k,k-1)x(k-1)+w(k,k-1) \tag{1}$$

where $x(k)\in R^{n\times 1}$ is the state vector, $\Phi(k,k-1)\in R^{n\times n}$ is the state transfer matrix, $w(k,k-1)\in R^{n\times 1}$ is white and Gaussian distributed process noise with zero mean and variance $Q(k,k-1)$.

Assuming there are N sensors with different sampling rate to observe the system process, the corresponding expressions of the measurement translated through the fading channel can be described as

$$z_i(k_i)=m_i(k_i)H_i(k_i)x(k_i)+v_i(k_i)\text{ , } i=1,2,\cdots,N_k \tag{2}$$

where $x(k_i)\in R^{n\times 1}$ is the state vector at the moment k_i, $z_i(k_i)\in R^{p_i\times 1}(p_i\le n)$ is the measurement sampled by sensor i at the moment k_i, $H_i(k_i)\in R^{p_i\times n}$ is the corresponding measurement matrix, $v_i(k_i) \in R^{p_i \times 1}$ is white and Gaussian distributed process noise with zero mean and variance $R_i(k_i)$ .The random variable $m_i(k_i)$ regulates the probabilistic fading phenomenon of the i^{th} sensor, which has the probability density function with mathematical expectation μ_i and variance M_i . N_k is the number of the measurement sampled in the fusion interval k .

Assumption 1: the process noise $w(k,k-1)$ is independent with the measurement noise $v_i(k_i)$ and the fading coefficient $m_i(k_i)$, namely

$$\begin{cases} E\left\{w(k,k-1)v_i^T(k_i)\right\}=0 \\ E\left\{v_i(k_i)v_j^T(l_j)\right\}=0, k\neq l, or\ i\neq j \\ E\left\{w(k,k-1)m_i^T(k_i)\right\}=0 \\ E\left\{m_i(k_i)v_i^T(k_i)\right\}=0 \end{cases} \tag{3}$$

Assumption 2: the initial state $x(0)$ is a random vector, which is independent with $w(k,k-1)$, $v_j(l)$ and satisfies

$$E\{x(0)\}=x_0 \tag{4}$$

$$E\left\{[x(0)-x_0][x(0)-x_0]^T\right\}=P_0 \tag{5}$$

Due to the difference of the sampling rate of N sensors, the fusion scenario in each fusion interval would be complex: in a fusion interval, there may be none, one or multiple measurements arrive at the fusion center. The fusion filter designed in the centralized frame needs to wait for all measurements sampled in the fusion interval arrive at the fusion center. Therefore, the centralized fusion methods for asynchronous multi-sensor fading measurements have strong high-dimension matrix computing requirement and poor real time property. In the sequential fusion frame, the measurement can be dealt with once it arrives at the fusion center. That can ensure the real time property of the fusion filtering. It is, therefore, our aim in this paper to make a major effort to address the asynchronous fusion filtering problem for multi-sensor fading measurements in the sequential fusion frame.

3. Main Result

In this section, we aim to establish a sequential fusion filter for asynchronous multi-sensor fading measurements, which can handle the fading measurement in time once it arrives at the fusion center, without waiting for other measurements. However, these measurements are sampled by the sensors with different sampling rate. As a result, the fading measurements arrive at the fusion center with different sampling time and different fading effects at different arriving time in a fusion interval. In order to estimate the discrete system states, all measurements should be transformed as the pseudo measurements of the fusion state in the current fusion interval.

3.1. Pseudo Measurement Transformation

According to the system state model (1), we can get

$$x(k)=\Phi(k,k_i)x(k_i)+w(k,k_i) \tag{6}$$

which is transformed as

$$x(k_i)=\Phi(k_i,k)(x(k)-w(k,k_i)) \tag{7}$$

Submit (7) into (2), the fading measurement can be described as

$$\begin{aligned} z_i(k_i) &= m_i(k_i)H_i(k_i)x(k_i)+v_i(k_i)=m_i(k_i)H_i(k_i)\Phi(k_i,k)(x(k)-w(k,k_i))+v_i(k_i) \\ &= m_i(k_i)H_i(k_i)\Phi(k_i,k)x(k)+v_i(k_i)-m_i(k_i)H_i(k_i)\Phi(k_i,k)w(k,k_i) \end{aligned} \tag{8}$$

Denote $H_i^m(k):=m_i(k_i)H_i(k_i)\Phi(k_i,k), v_i^m(k):=v_i(k_i)-H_i^m(k)w(k,k_i)$, $z_i^m(k):=z_i(k_i)$, then

$$z_i^m(k)=H_i^m(k)x(k)+v_i^m(k) \tag{9}$$

Here $z_i^m(k)$ is the pseudo measurements of the fusion state $x(k)$ the fusion interval k, and the corresponding pseudo measurement noise $v_i^m(k)$ satisfies the following statistical properties

$$\begin{cases} E\left\{\begin{pmatrix} w(k,k-1) \\ v_i^m(k) \end{pmatrix}[w^T(l,l-1)\,(v_j^m(k))^T]\right\}=\begin{bmatrix} Q(k,k-1) & b_j(k) \\ b_i^T(k) & S_{ij}(k) \end{bmatrix}\delta_{k,l} \\ E\{v_i^m(k)\}=E\{v_i(k_i)-H_i^m(k)w(k,k_i)\}=0 \end{cases} \tag{10}$$

in which,

$$\begin{cases} \bar{H}_i(k)=E\{H_i^m(k)\}\hat{=}\mu_i(k)H_i(k_i)\Phi(k_i,k) \\ b_i(k)=E\{w(k,k-1)(v_i^m(k))^T\}=-Q(k,k_i)(\bar{H}_i(k))^T \\ S_{ij}(k)=\bar{H}_i(k)Q(k,k_i,k_j)(\bar{H}_j(k))^T \end{cases} \tag{11}$$

$$Q(k,k_i,k_j)=E\{w(k,k_i)w^T(k,k_j)\}=\begin{cases} Q(k,k_i),k_i\ge k_j \\ Q(k,k_j),k_i<k_j \end{cases} \tag{12}$$

As shown in (12), the autocorrelations during the pseudo measurement noises and the cross correlations of the pseudo measurement noises and the process noise are no longer satisfy (3). This makes that the predicted values of fading measurements and the filter gains are more difficultly solved. In this section, a noise estimation skill is adopted to give an unbiased predicted value of each fading measurement and the corresponding optimal filter gain in the sense of LMMSE.

3.2. Sequential Fusion filtering

Denote the global state estimate at moment $k-1$ as $\hat{x}(k-1|k-1)$, which is an unbiased estimate of $x(k-1)$ and the corresponding estimate error covariance is $P(k-1|k-1)$, then the prediction of the fusion state $x(k)$ the fusion interval k and the corresponding prediction error covariance at moment k are given by

$$\begin{cases} \hat{x}(k|k-1) = \Phi(k,k-1)\hat{x}(k-1|k-1) \\ P(k|k-1) = \Phi(k,k-1)P(k-1|k-1)\Phi^T(k,k-1) + Q(k,k-1) \end{cases} \tag{13}$$

In the sequential fusion frame, the state prediction at moment k can be regarded as the beginning of the fusion process. Therefore, let

$$\hat{x}_0(k|k) = \hat{x}(k|k-1); P_0(k|k) = P(k|k-1) \tag{14}$$

Remark 1: It's easy to get that $\hat{x}_0(k|k)$ is an unbiased estimate of $x(k)$, due to the unbiased $\hat{x}(k-1|k-1)$.

When $z_1(k_1)$ arrives at fusion center, it is transformed as the pseudo measurement of $x(k)$, which is denoted as $z_1^m(k)$. Denoting a prediction of $z_1^m(k)$ as $\hat{z}_1^m(k|k-1) := E\{z_1^m(k)|Z^{k-1}\}$, where $Z^{k-1} = \{z_1^{N_1}, z_1^{N_2}, \cdots, z_1^{N_{k-1}}\}$, $z_1^{N_j} = \{z_1(j_1), z_2(j_2), \cdots, z_{N_j}(j_{N_j})\}$, $j = 1, 2, \cdots, k-1$, an unbiased form of which can be obtained by the following lemma.

Lemma 1. An unbiased prediction of the pseudo measurement $z_1(k_1)$ is $\hat{z}_1^m(k|k-1) = \bar{H}_1(k)\hat{x}_0(k|k)$.

Proof. Substitute (9) into the definition $\hat{z}_1^m(k|k-1)$, we can get

$$\begin{aligned} \hat{z}_1^m(k|k-1) &= E\{z_1^m(k)|Z^{k-1}\} \\ &= E\{H_1^m(k)x(k) + v_1^m(k)|Z^{k-1}\} \\ &= \bar{H}_1(k)\hat{x}_0(k|k) \end{aligned} \tag{15}$$

Let $\tilde{z}_1^m(k|k-1) := z_1^m(k) - \hat{z}_1^m(k|k-1)$, then according to (3),

$$\begin{aligned} E\{\tilde{z}_1^m(k|k-1)\} &= E\{z_1^m(k) - \hat{z}_1^m(k|k-1)\} \\ &= E\{H_1^m(k)x(k) + v_1^m(k) - \bar{H}_1(k)\hat{x}_0(k|k)\} \\ &= E\{\bar{H}_1(k)x(k) - \tilde{H}_1^m(k)x(k) + v_1^m(k) - \bar{H}_1(k)\hat{x}_0(k|k)\} \\ &= \bar{H}_1(k)E\{\tilde{x}_0(k|k)\} - E\{\tilde{H}_1^m(k)\}E\{x(k)\} + E\{v_1^m(k)\} \end{aligned} \tag{16}$$

where $\tilde{H}_1^m(k) = H_1^m(k) - \bar{H}_1(k)$.

Due to Remark 1, $E\{\tilde{H}_1^m(k)\} = E\{H_1^m(k) - \bar{H}_1(k)\} = 0$ and (10), $E\{\tilde{z}_1^m(k|k-1)\} = 0$. This means that (15) is an unbiased prediction. The proof is now completed.

Then, (14) can be updated by the following filter with the pseudo measurement $z_1^m(k)$, the filter gain in which is strictly deduced in the sense of LMMSE.

Sub-filter1:

$$\begin{cases} \hat{x}_1(k|k) = \hat{x}_0(k|k) + K_1(k)(z_1^m(k) - \hat{z}_1^m(k|k-1)) \\ P(k|k) = P_0(k|k) - K_1(k)P_{xz1}^T(k|k-1) \end{cases} \tag{17}$$

in which,

$$K_1(k) = P_{xz1}(k|k-1)P_{zz1}^{-1}(k|k-1) \tag{18}$$

$$\begin{aligned} P_{xz1}(k|k-1) &= E\{\tilde{x}_1(k|k-1)(\tilde{z}_1^m(k|k-1))^T\} \\ &= E\{\tilde{x}_1(k|k-1)(H_1^m(k)x(k)+v_1^m(k)-\bar{H}_1(k)\hat{x}_0(k|k))^T\} \\ &= P_0(k|k)\bar{H}_1^T(k)+b_1(k) \end{aligned} \tag{19}$$

$$P_{zz1}(k|k-1) = \bar{H}_1(k)P(k|k-1)\bar{H}_1^T(k)+\bar{H}_1(k)b_1(k)+(\bar{H}_1(k)b_1(k))^T+S_{11}(k) \tag{20}$$

Remark 2: $\hat{x}_1(k|k)$ in Sub-filter1 is unbiased, due to Remark 1 and Lemma 1.

When $z_j(k_j),\ j=2,\cdots,N_k$ arrives at the fusion center, it can be transformed as the pseudo fading measurement $z_j^m(k)$, which is utilized to update $\hat{x}_{j-1}(k|k)$ by the following filter.

Sub-filter *j*:

$$\begin{cases} \hat{x}_j(k|k) = \hat{x}_{j-1}(k|k)+K_j(k)(z_j^m(k)-\hat{z}_j^m(k|k-1)) \\ P_j(k|k) = P_{j-1}(k|k)-K_j(k)P_{xzj}^T(k|k-1) \end{cases} \tag{21}$$

Where

$$K_j(k) = P_{xzj}(k|k-1)P_{zzj}^{-1}(k|k-1) \tag{22}$$

$$P_{xzj}(k|k-1) = P_{j-1}(k|k)\bar{H}_j^T(k)+P_{xvj}(k|k-1) \tag{23}$$

$$P_{zzj}(k|k-1) = \bar{H}_j(k)P_{j-1}(k|k)\bar{H}_j^T(k)+\bar{H}_j(k)P_{xvj}(k|k-1)-P_{w\hat{v}j}(k|k-1)+(\bar{H}_j(k)P_{xvj}(k|k-1))^T+S_{jj}(k) \tag{24}$$

In order to design an unbiased $\hat{x}_j(k|k)$ based on the unbiased $\hat{x}_{j-1}(k|k)$, $\hat{z}_j^m(k|k-1)$ should be an unbiased prediction of the pseudo fading measurement $z_j^m(k)$.

$$\begin{aligned} \hat{z}_j^m(k|k-1) &= E\{z_j^m(k)|Z^{k-1},z_1(k_1),z_2(k_2),\cdots,z_{j-1}(j-1)\} \\ &= E\{H_j^m(k)x(k)+v_j^m(k)|Z^{k-1},z_1^{j-1}\} \\ &= \bar{H}_j(k)\hat{x}_{j-1}(k|k)+\hat{v}_j^m(k|k-1) \end{aligned} \tag{25}$$

It is different from the traditional Kalman filters that the unbiased $\hat{v}_j^m(k|k-1)$ in (25) is nonzero, due to the cross correlation during the pseudo measurement noises $v_i^m(k)$, $i=1,\cdots,j-1$ and $w(k,k-1)$, and the auto correlation during the pseudo measurement noises $v_i^m(k)$, $i=1,\cdots,j-1$. Similar to the state estimation in Kalman filter, the following estimation skill is adopted to estimate the pseudo measurement noise $v_j^m(k)$ on the condition of $\{Z^{k-1},z_1^{j-1}\}$, which is strictly deduced in the sense of LMMSE to ensure the unbiasedness.

$$\hat{v}_j^m(k|k-1) = -\bar{H}_j(k)\hat{w}_j(k,k_j|k-1) \tag{26}$$

$$\hat{w}_j(k,k_j|k-1)=\hat{w}_{j-1}(k,k_j|k-1)+P_{wz,j-1}(k,k_j|k-1)P_{zzj-1}^{-1}(k|k-1)(z_{j-1}^m(k)-\hat{z}_{j-1}^m(k|k-1)) \tag{27}$$

$$\begin{aligned}P_{wz,j-1}(k,k_j|k-1)&\hat{=}E\{w(k,k_j)(\tilde{z}_{j-1}^m(k|k-1))^T\}\\&=P_{xwj-1}(k,k_j|k-1)\bar{H}_{j-1}^T(k)+E\{w(k,k_{j-1})(v_{j-1}^m(k))^T\}-E\{w(k,k_{j-1})(\hat{v}_{j-1}^m(k|k-1))^T\}\end{aligned} \tag{28}$$

$$\begin{aligned}P_{xwj}(k,k_j|k-1)&\hat{=}E\{\tilde{x}_{j-1}(k|k)(w(k,k_j))^T\}\\&=(I-K_{j-1}(k)\bar{H}_{j-1}(k))P_{xwj-2}(k,k_j|k-1)+K_{j-1}(k)E\{v_{j-1}^m(k)(w(k,k_j))^T\}-K_{j-1}(k)E\{\hat{v}_{j-1}^m(w(k,k_j))^T\}\end{aligned} \tag{29}$$

$$E\{v_{j-1}^m(k)(w(k,k_j))^T\}=-\bar{H}_{j-1}(k)Q(k,k_{j-1},k_j) \tag{30}$$

$$E\{\hat{v}_{j-1}^m(k|k)(w(k,k_j))^T\}=-\bar{H}_{j-1}(k)P_{\hat{w}wj-1}(k,k_j|k-1) \tag{31}$$

$$P_{\hat{w}wj-1}(k,k_j|k-1)=E\{\hat{w}_{j-2}(k,k_j|k-1)(w(k,k_j))^T\}+P_{wz,j-2}(k,k_j|k-1)P_{zzj-2}^{-1}(k|k-1)P_{wz,j-2}^T(k,k_j|k-1) \tag{32}$$

$$\begin{aligned}P_{wz,j-2}(k,k_j|k-1)&\hat{=}E\{w(k,k_j)(\tilde{z}_{j-2}^m(k|k-1))^T\}\\&=P_{xwj-2}(k,k_j|k-1)\bar{H}_{j-2}^T(k)+E\{w(k,k_{j-1})(v_{j-2}^m(k))^T\}-E\{w(k,k_{j-1})(\hat{v}_{j-2}^m(k|k-1))^T\}\end{aligned} \tag{33}$$

And the covariance $P_{xvj}(k|k-1)$ and $P_{v\hat{v}j}(k|k-1)$ in (23), (24) can be obtain by

$$P_{xvj}(k|k-1)=-P_{xwj}(k,k_j|k-1)\bar{H}_j^T(k) \tag{34}$$

$$P_{v\hat{v}j}(k|k-1)=\bar{H}_j(k)E\{w(k,k_j)(\hat{w}_j(k,k_j|k-1))^T\}\bar{H}_j^T(k)=\bar{H}_j(k)P_{w\hat{w}j}(k,k_j|k-1)\bar{H}_j^T(k) \tag{35}$$

In the above iteration, the boundary conditions are: $\hat{w}_0(k,k_j|k-1)=0$, $Q(k,k_0,k_j)=0$, $E\{v_0^m(k)(\bar{v}_j^m(k))^T\}=0$, $P_{xw0}(k,k_j|k-1)=0$, $P_{\hat{w}w0}(k,k_{j-1}|k-1)=0$.

When $j=N_k$, the global state estimate and its corresponding error covariance at moment k can be given by

$$\hat{x}(k|k)=\hat{x}_{N_k}(k|k),P(k|k)=P_{N_k}(k|k) \tag{36}$$

The sequential fusion method is composed of **Sub-filter1**, **Sub-filter2**, $\cdots$,**Sub-filter** N_k, and (36).

4. Simulation

In this section, a numerical example is presented to illustrate the effectiveness of the proposed sequential fusion filtering method for asynchronous multi-sensor fading measurements, which is compared with the centralized fusion method.

Consider the following discrete time constant velocity motion model with random perturbations:

$$x(k)=\begin{bmatrix}1 & T\\0 & 1\end{bmatrix}x(k-1)+w(k,k-1) \tag{37}$$

where $T = 1s$ is the fusion interval, $w(k,k-1)$ is zero mean Gaussian white noise with the variance

$$Q(k,k-1) = \begin{bmatrix} T^3/3 & T^2/2 \\ T^2/2 & T \end{bmatrix} \cdot q \tag{38}$$

in which, $q = 0.15$ is the target motion disturbance parameters.

The measurements sampled by two sensors can be described by following function, which are translated through fading channels to the fusion center.

$$z_i(k_i) = m_i(k_i) H_i(k_i) x(k_i) + v_i(k_i), \quad i = 1,2 \tag{39}$$

in (39), the zero mean Gaussian measurement noises $\boldsymbol{v}_i(k_i)$, $i = 1,2$ are with variances $R_1(k_1) = 0.1$, $R_2(k_2) = 0.1$. The measurement matrix $H_1(k_1) = [0.9,1]$, $H_2(k_2) = [1.0,0.5]$.

The probability density function for $m_i(k_i)$ is given by:

$$p_i(s) = \begin{cases} 0.05, & s = 0 \\ 0.10, & s = 0.5 \\ 0.85, & s = 1 \end{cases}, \quad i = 1,2 \tag{40}$$

Obviously, the expectation and variance of $p_i(s)$ can be obtained as 0.9 and 0.065.

The asynchronous sampling scenario: For Sensor 1, the sampling interval is 0.5s, and Senor 1 starts its tracking process at the initial time. For Sensor 2, the sampling interval is 0.5s, and Senor 1 starts its tracking process at the moment, which is 1s after the initial time.

Set the initial value as $x_0 = [10,1]$, and $P_0 = 0.1 \times \begin{bmatrix} 1 & 1/T \\ 1/T & 2/T^2 \end{bmatrix}$.In this simulation, the centralized fusion method is shortened to CFM, the proposed sequential fusion method is abbreviated to SFM. The simulation results are given in Table 1 and Figure 1-2.

Table 1. The Mean Absolute Estimate Error Means & Filtering Time

	Position	Velocity	Mean Filtering time
CFM	0.4842	0.065	0.031
SFM	0.4842	0.065	0.016

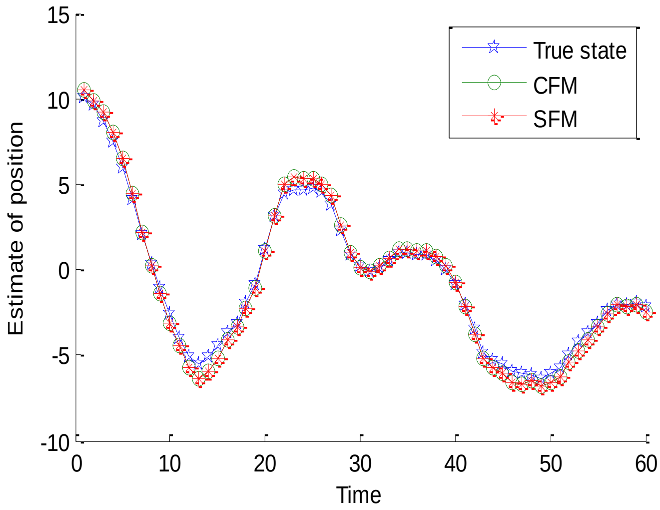

Figure 1. True State Curve and Estimate Curves of Position

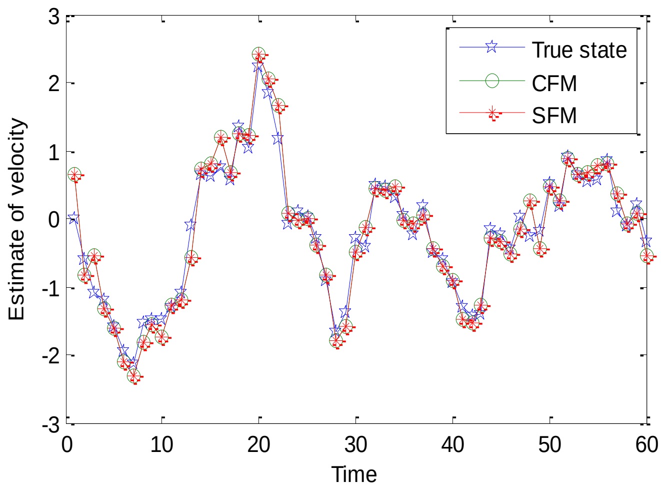

Figure 2. True State Curve and Estimate Curves of Velocity

As shown in the simulation results above, it is verified the functional equivalence of CFM and SFM that they have the same estimated accuracy as illustrated in Figure 1-2 and Table 1. This means that the proposed sequential fusion method can effectively deal with the fusion filtering problems for fading measurements sampled asynchronously by multi-sensor systems.

Furthermore, Due to the sequential fusion strategy, SFM could estimate the interested signal with each measurement once it arrives at the fusion center, without waiting for the measurement all received by the fusion center. Therefore, the mean filtering time of SFM is shorter than CFM. It indicated that SFM is a real time robust fusion filter.

5. Conclusions

In this paper, a sequential fusion filtering algorithm has been proposed for the fading measurements sampled asynchronously by multi-sensor systems, the probabilistic fading phenomenon of which is described by statistical means and variances. In the fusion center, the asynchronous fading measurements are firstly transformed into pseudo fading measurements of the fusion state in the current fusion interval. Then, these pseudo fading measurements are handled sequentially in their arriving sequence by utilizing a novel noise estimation skill to deal with the correlations during pseudo measurement noises, which is strictly deduced in the sense of LMMSE. The unbiasedness of the proposed fusion filtering method has also been analyze. The final simulation illustrates the effectiveness of the proposed sequential fusion filtering method for asynchronous multi-sensor fading measurements

It is assumed in this paper that the multi-sensor system is described by a linear mathematical model. However, the nonlinear system is more interesting in many real applications. Therefore, the extension of the proposed theory to the sequential fusion filtering in the same framework for asynchronous multi-sensor nonlinear systems with fading measurements is in the investigation.

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