Research Article

Weighted Measurement Fusion Quantized Filtering with Bandwidth Constraints and Missing Measurements in Sensor Networks

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This paper is concerned with the estimation problem of a dynamic stochastic variable in a sensor network, where the quantization of scalar measurement, the optimization of the bandwidth scheduling, and the characteristic of transmission channels are considered. For the imperfect channels with missing measurements in sensor networks, two weighted measurement fusion (WMF) quantized Kalman filters based on the quantized measurements arriving at the fusion center are presented. One is dependent on the known message of whether a measurement is received. The other is dependent on the probability of missing measurements. They have the reduced computational cost and same accuracy as the corresponding centralized fusion filter. The approximate solution for the optimal bandwidth-scheduling problem is given under a limited bandwidth constraint. Furthermore, the vector measurement case is also discussed. The simulation research shows the effectiveness.

1. Introduction

In recent years, sensor networks have been widely investigated in decentralized estimation, detection, and control due to the significant applications in environmental monitoring, intelligent transportation, space exploration, and so forth [1]. In wireless sensor networks (WSN), a large number of sensors are spatially distributed to monitor the signal of interest. Each sensor makes a measurement of the signal and transmits it to the fusion center (data processing center). Due to a bandwidth constraint, each sensor is only able to transmit a finite number of bits. So the measurement must be quantized to adapt the limited bandwidth before it is transmitted. Due to the imperfection of networks, the quantized measurement can be lost during the transmission. Then the fusion centre will use the quantized measurements received to obtain a fusion estimate of the signal. WSN introduce many interesting research topics such as information fusion [2], network lifetime maximization [3], sensor coverage or scheduling [4], and optimization with bandwidth or energy-efficient constraints [5].

Various algorithms have been proposed for network estimation, detection, and control [5–18]. Decentralized detection is investigated in a sensor network where the communication channels between sensors and the fusion centre are bandwidth constrained [5]. Several distributed estimators for parameters have been designed in the presence of additive sensor noise [6–10]. A universal decentralized estimator taking into account local SNR and channel path loss in sensor networks is studied [11] where the power scheduling optimization is solved based on the Karush-Kuhn-Tucker (KKT) condition. Quantization approach in many references above is to quantize the sensor's measurements directly. A distributed estimation approach based on the sign of innovations (SOI) is developed in [12] where only the transmission of a single bit per measurement is required. However, the cost of saving more communication is more accuracy loss. As a generalization of [12], a multilevel quantized innovation filter is presented [13, 14]. The estimation and control based on the logarithm quantization approach are studied in [15, 16]. Quantized Kalman filters based on quantized scalar measurements and innovations are presented for perfect channels in sensor networks [17], respectively. However, the quantized estimation for imperfect channels with missing measurements is not taken into consideration. A centralized

fusion quantized filter dependent on the packet dropout rate is designed for sensor networks with packet dropouts [18]. However, it has the expensive computational burden due to the augmented measurements.

In this paper, the quantized estimation problem for a dynamic stochastic variable is studied in a sensor network. Due to the limited bandwidth constraint, the measurement of sensors is quantized uniformly according to a given optimal bandwidth scheduling. During the transmission of quantized measurements, there are possible losses due to imperfect channels. Due to the large number of data, the fusion center compresses the received measurements to produce a reduced dimensional fused measurement, based on which, two weighted measurement fusion quantized filters are presented. One is dependent on the knowledge of whether a packet is received. The other is dependent on the probabilities of missing measurements. The front has the better accuracy since more messages are used. They have the same accuracy as the corresponding centralized fusion filters.

2. Problem Formulation

Consider the discrete-time system in a sensor network with N sensors

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

$$y_i(t) = h_i(t) x(t) + v_i(t), \quad i = 1, 2, \ldots, N, \tag{2}$$

where $x(t) \in R^n$ is the state to be estimated, $y_i(t) \in R$ is the scalar measurement of the ith sensor, N is the number of sensors, and $\Phi(t)$, $\Gamma(t)$, $h_i(t)$ are time-varying matrices with appropriate dimensions.

Assumption 1. $w(t) \in R^r$ and $v_i(t) \in R$, $i = 1, 2, \ldots, N$ are uncorrelated white noises with zero mean and variances $Q_w(t)$ and $\sigma_{v_i}^2(t)$. The initial value $x(0)$ with mean μ_0 and variance P_0 is uncorrelated with $w(t)$ and $v_i(t)$.

Assumption 2. $y_i(t) \in [\underline{U}_i, \overline{U}_i]$, where $\underline{U}_i$ and $\overline{U}_i$, $i = 1, 2, \ldots, N$, are known constants.

The estimation problem considered is shown in Figure 1. Each sensor makes a measurement $y_i(t)$. Due to the limited bandwidth, it is quantized to produce a quantized measurement $m_i(t) = q(y_i(t))$ where $q(\cdot)$ is a quantized function. Then, $m_i(t)$ is transmitted to the fusion center by an imperfect channel where there are possible packet losses. We introduce a Bernoulli distributed random variable $\gamma_i(t)$ with the probabilities Prob$\{\gamma_i(t) = 1\} = \alpha_i$ and Prob$\{\gamma_i(t) = 0\} = 1 - \alpha_i$ to describe the phenomena of missing measurements. Namely, the data received by the fusion center is $m_i'(t) = \gamma_i(t) m_i(t)$, where $\gamma_i(t) = 1$ means the quantized measurement is received and $\gamma_i(t) = 0$ means loss. At last, the fusion center will combine the received data $m_i'(t)$ to give a final estimate for state $x(t)$. We assume that the fusion center knows all the parameters of system (1). If there is a sufficient bandwidth to be supplied and the channel is perfect, that is, in the case of $m_i'(t) = y_i(t)$, the standard Kalman filter can be used [19]. If the bandwidth is limited and the channel is perfect, that

is, in the case of $m_i'(t) = m_i(t)$, the fusion center will make the estimate based on the received measurements $\{m_i(t), i = 1, 2, \ldots, N\}$. Otherwise, the fusion center has to make the estimate based on the received measurements $\{m_i'(t), i = 1, 2, \ldots, N\}$.

Our aim in this paper is to find the weighted measurement fusion quantized Kalman filters (WMF-QKF) under the limited bandwidth by imperfect channels. Two kinds of filters are designed. One is dependent on the values of $\gamma_i(t)$, the other is dependent on the probability of $\gamma_i(t)$.

3. WMF-QKF

3.1. Quantization and Bandwidth Scheduling.
We adopt the uniform quantization strategy in [11]. Measurement $y_i(t)$ is quantized to $m_i(t)$ with the length of $b_i(t)$ bits, where $b_i(t)$ is to be determined later. We have $2^{b_i(t)}$ quantization points spaced uniformly within the interval $[\underline{U}_i, \overline{U}_i]$. The quantization noise $n_i(t) = m_i(t) - y_i(t)$ is uncorrelated white noise with zero mean and variance $\sigma_{n_i}^2(t) = \mathrm{E}(n_i(t))^2 = \mathrm{E}(m_i(t) - y_i(t))^2 \leq \delta_i^2(t)$ where $\delta_i^2(t) = (\overline{U}_i - \underline{U}_i)^2/[4(2^{b_i(t)} - 1)^2]$. Furthermore, $n_i(t)$, $v_i(t)$, $i = 1, 2, \ldots, N$, and $w(t)$ are uncorrelated with each other.

In sensor networks, the whole bandwidth of communication channels is bounded. Let B be the bits of the whole bandwidth and let $b_i(t)$ be the bits scheduled to the ith sensor. To obtain the good estimation performance under the constraint of bounded bandwidths, we adopt the following bandwidth scheduling strategy [17]:

$$\min \quad \sum_{i=1}^{N} \frac{h_i(t) h_i^T(t)}{\sigma_{v_i}^2(t)} \delta_i^2(t)$$

$$\text{s.t.} \quad \sum_{i=1}^{N} b_i(t) \leq B, \quad b_i(t) \geq 0, \ i = 1, 2, \ldots, N, \tag{3}$$

where $h_i(t) h_i^T(t)/\sigma_{v_i}^2(t)$ is the SNR (signal to noise ratio). Then the optimal solution of $b_i(t)$ is given as

$$b_i(t) = \left\lceil \log_2\left(\frac{\sqrt{\ln 2 h_i(t) h_i^T(t)} \left(\overline{U}_i - \underline{U}_i\right)}{\sigma_{v_i}(t) \sqrt{2\lambda(t)}} \right) \right\rceil,$$

$$\lambda(t) = \frac{\ln 2/2 \prod_{i=1}^{N}\left(h_i(t) h_i^T(t) \left(\overline{U}_i - \underline{U}_i\right)^2 / \sigma_{v_i}^2(t) \right)^{1/N}}{2^{2B/N}}, \tag{4}$$

where the symbol $\lceil \cdot \rceil$ denotes the least integer greater than $\cdot$.

3.2. Design of Two Kinds of WMF-QKF

3.2.1. Filter Design Dependent on Values of $\gamma_i(t)$.
When the values of $\gamma_i(t)$ are known, that is, we know whether a packet is received or lost, which can be carried out by the information of time stamps, letting $L(t)$ be the number of measurements received by the fusion center at t time, then we have the augmented measurement equation in the fusion center:
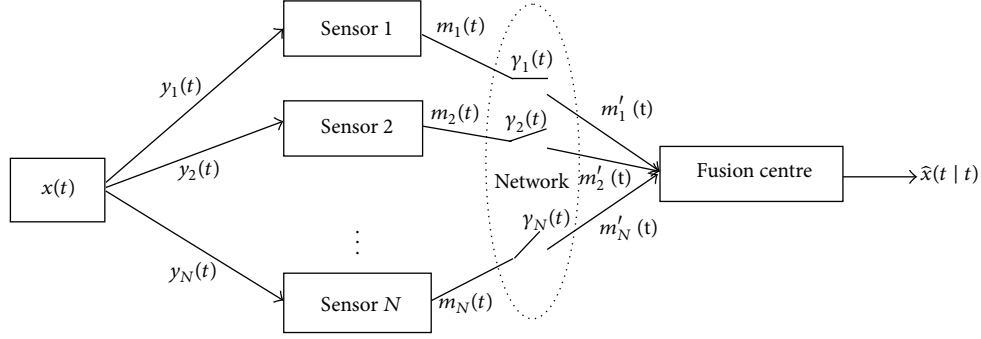
$$m'(t) = h(t) x(t) + \eta(t), \tag{5}$$

FIGURE 1: Distributed state estimation scheme based on quantized observations.

where the augmented quantized measurement received by the fusion center is $m'(t) = [m'_{k_1(t)}(t), m'_{k_2(t)}(t), \ldots, m'_{k_{L(t)}(t)}(t)]^T$, $1 \leq k_1(t) < \cdots < k_{L(t)}(t) \leq N$ and the integer $k_i(t)$ denotes the $k_i(t)$th sensor that arrives at the fusion center. The augmented measurement matrix is $h(t) = [h^T_{k_1(t)}(t), h^T_{k_2(t)}(t), \ldots, h^T_{k_{L(t)}(t)}(t)]^T$ and the noise is $\eta(t) = [\eta_{k_1(t)}(t), \eta_{k_2(t)}(t), \ldots, \eta_{k_{L(t)}(t)}(t)]^T$ with zero mean and variance matrix $Q_\eta(t) = \text{diag}(\sigma^2_{\eta_{k_1(t)}}(t), \sigma^2_{\eta_{k_2(t)}}(t), \ldots, \sigma^2_{\eta_{k_{L(t)}(t)}}(t))$ where $\eta_{k_i(t)}(t) = v_{k_i(t)}(t) + n_{k_i(t)}(t)$ are uncorrelated with one another, with zero mean and variance $\sigma^2_{\eta_{k_i(t)}}(t) = \sigma^2_{v_{k_i(t)}}(t) + \sigma^2_{n_{k_i(t)}}(t) \leq \sigma^2_{v_{k_i(t)}}(t) + \delta^2_{k_i(t)}(t)$. We approximately consider the measurement noise $\eta(t)$ to be the white noise. Then, the Kalman filtering can be used for the augmented systems (1) and (5) where the upper bound of variance of the quantized noise is used. However, the expensive computational cost is required due to the high-dimensional augmented measurement when the data of a large number of sensors arrive at the fusion center. To reduce the computational cost, we will present the WMF filter in the following text.

When $L(t) \geq 1$, that is, there are measurement data arriving at the fusion center at time t, then we can obtain the filter according to the following three cases.

(a) If $h(t)$ is full row rank, we can apply the standard Kalman filtering algorithm to obtain the fusion filter.

(b) If $h(t)$ is full column rank, we have that $h^T(t)Q^{-1}_\eta(t)h(t)$ is nonsingular. Then the WMF measurement equation is given as follows:

$$\overline{m}(t) = x(t) + \overline{\eta}(t), \tag{6}$$

where $\overline{m}(t) = [h^T(t)Q^{-1}_\eta(t)h(t)]^{-1}h^T(t)Q^{-1}_\eta(t)m'(t)$, $\overline{\eta}(t) = [h^T(t)Q^{-1}_\eta(t)h(t)]^{-1}h^T(t)Q^{-1}_\eta(t)\eta(t)$, $\overline{Q}^{-1}_\eta(t) = [h^T(t)Q^{-1}_\eta(t)h(t)]^{-1}$.

Then based on systems (1) and (6), we can apply the standard Kalman filtering algorithm to obtain the fusion filter.

(c) If $h(t)$ is not full rank, that is, $h^T(t)Q^{-1}_\eta(t)h(t)$ is singular, letting rank$\{h(t)\} = p(t)$, $p(t) \leq \min\{n, L(t)\}$, then there is full-rank decomposition [20]; that is,

$$h(t) = f(t)\overline{h}(t), \tag{7}$$

where $f(t) \in R^{L(t) \times p(t)}$ is full column rank and $\overline{h}(t) \in R^{p(t) \times n}$ is full row rank. $f^T(t)Q^{-1}_\eta(t)f(t)$ is a nonsingular matrix. So, we have the WMF measurement equation as

$$\overline{\overline{m}}(t) = \overline{h}(t)x(t) + \overline{\overline{\eta}}(t), \tag{8}$$

where $\overline{\overline{m}}(t) = [f^T(t)Q^{-1}_\eta(t)f(t)]^{-1}f^T(t)Q^{-1}_\eta(t)m'(t)$, $\overline{\overline{\eta}}(t) = [f^T(t)Q^{-1}_\eta(t)f(t)]^{-1}f^T(t)Q^{-1}_\eta(t)\eta(t)$, $Q_{\overline{\overline{\eta}}}(t) = [f^T(t)Q^{-1}_\eta(t)f(t)]^{-1}$.

Then based on systems (1) and (8), we can apply the standard Kalman filtering algorithm to obtain the fusion filter.

When $L(t) = 0$, that is, there are no measurement data arriving at the fusion center at time t, then, the Kalman predictor is used based on the last estimator.

Remark 3. From (6) and (8), we can know that the dimension of the compressed measurement $\overline{m}(t)$ or $\overline{\overline{m}}(t)$ is not greater than $\min\{n, L(t)\}$. When the number of sensors arriving at the fusion center is large, that is, $L(t) \gg n$, the proposed WMF-QKF with the computational order of magnitude $O(p^3(t))$ can obviously reduce the computational cost compared to the centralized fusion filter with the computational order of magnitude $O(L^3(t))$. However, they have the same accuracy; that is, WMF-QKF has the global optimality [20].

3.2.2. Filter Design Dependent on Probabilities of $\gamma_i(t)$. In this section, we will design the filter dependent on the probabilities of $\gamma_i(t)$. At each time, the measurement of each sensor arriving at the fusion center can be expressed as follows:

$$\begin{aligned} m'_i(t) &= \gamma_i(t)m_i(t) \\ &= \gamma_i(t)h_i(t)x(t) + \gamma_i(t)v_i(t) \\ &\quad + \gamma_i(t)n_i(t), \quad i = 1, 2, \ldots, N \end{aligned} \tag{9}$$

which can be rewritten as

$$m'_i(t) = \alpha_i h_i(t)x(t) + \zeta_i(t), \quad i = 1, 2, \ldots, N, \tag{10}$$

where $\zeta_i(t) = (\gamma_i(t) - \alpha_i)h_i(t)x(t) + \gamma_i(t)v_i(t) + \gamma_i(t)n_i(t)$, $i = 1, 2, \ldots, N$ are uncorrelated white noises with zero mean and

variances $\sigma_{\zeta_i}^2(t) = \alpha_i(1 - \alpha_i)h_i(t)q(t)h_i^T(t) + \alpha_i\sigma_{v_i}^2(t) + \alpha_i\sigma_{n_i}^2(t)$; $q(t) = E[x(t)x^T(t)]$ is the state second-order moment which can be computed by $q(t+1) = \Phi(t)q(t)\Phi^T(t) + \Gamma(t)Q_w(t)\Gamma^T(t)$ from (1).

Then the augmented measurements can be expressed as

$$M'(t) = \tilde{h}(t)x(t) + \zeta(t), \tag{11}$$

where $M'(t) = [m_1'(t)\ m_2'(t)\ \cdots\ m_N'(t)]^T$, $\tilde{h}(t) = [\alpha_1 h_1(t)\ \alpha_2 h_2(t)\ \cdots\ \alpha_N h_N(t)]^T$, $\zeta(t) = [\zeta_1(t)\ \zeta_2(t)\ \cdots\ \zeta_N(t)]^T$; $\zeta(t)$ and $w(t)$ are uncorrelated. The variance matrix of $\zeta(t)$ is $Q_\zeta(t) = \text{diag}\left(\sigma_{\zeta_1}^2(t)\ \sigma_{\zeta_2}^2(t)\ \cdots\ \sigma_{\zeta_N}^2(t)\right)$ where the symbol diag$(\cdot)$ denotes the diagonal matrix.

According to the different cases that the matrix $\tilde{h}(t)$ is full row-rank, full column-rank, or not full-rank, we can obtain the WMF-QKF dependent on probabilities of $\gamma_i(t)$ similar to design of the above subsection.

Remark 4. Two kinds of WMF-QKFs have been proposed. The filter dependent on the values of $\gamma_i(t)$ (WMF-QKFV) has better accuracy than that dependent on the probabilities of $\gamma_i(t)$ (WMF-QKFP) since more information is used. However, WMF-QKFV requires the online computation since it is dependent on the stochastic variable $\gamma_i(t)$ at each time. WMF-QKFP can be computed offline since it is only dependent on the probabilities. Moreover, WMF-QKFP has the reduced online computational cost than WMF-QKFV.

3.3. Multiple Dimension Measurement Case. WMF-QKF with optimization problems has been solved for systems with scalar measurement in Sections 3.1 and 3.2. In this section, we consider the WMF-QKF for systems with multiple dimension measurements. We consider the system

$$x(t+1) = \Phi(t)x(t) + \Gamma(t)w(t)$$
$$y_i(t) = H_i(t)x(t) + v_i(t), \quad i = 1, 2, \ldots, N, \tag{12}$$

where $y_i(t) \in R^{q_i}$ is the measurement vector of the ith sensor; other variables have the same definitions as Section 2. $H_i(t)$ is full row rank. We make the following assumptions.

Assumption 5. $w(t) \in R^r$ and $v_i(t) \in R^{q_i}$, $i = 1, 2, \ldots, N$, are uncorrelated white noises with zero mean and variance matrices $Q_w(t)$ and $Q_{v_i}(t)$, and their each component is uncorrelated with each other; that is, $Q_w(t)$ and $Q_{v_i}(t)$ are diagonal matrices.

Assumption 6. $y_i^{(k)}(t) \in [\underline{U}_i^{(k)}, \overline{U}_i^{(k)}]$, $k = 1, 2, \ldots, q_i$; $i = 1, 2, \ldots, N$, where $y_i^{(k)}(t)$ is the kth component of observation vector $y_i(t)$ and $\underline{U}_i^{(k)}$ and $\overline{U}_i^{(k)}$ are known constants.

The system structure is similar to Figure 1. For each component $y_i^{(k)}(t)$ of measurement $y_i(t)$ from the ith sensor, we quantize each component $y_i^{(k)}(t)$ to $m_i^{(k)}(t)$ with the length of $b_i^{(k)}(t)$ bits according to the quantized approach in

Section 3.1. Let the quantized noise be $n_i^{(k)}(t) = m_i^{(k)}(t) - y_i^{(k)}(t)$; then the variance of the quantized noise $n_i^{(k)}(t)$ is $\sigma_{n_i^{(k)}}^2(t) \leq \delta_{n_i^{(k)}}^2(t)$, $\delta_{n_i^{(k)}}^2(t) = (\overline{U}_i^{(k)} - \underline{U}_i^{(k)})^2/[4(2^{b_i^{(k)}(t)} - 1)^2]$. Furthermore, $n_i^{(k)}(t)$, $v_j^{(l)}(t)$, $i, j = 1, 2, \ldots, N$; $k = 1, 2, \ldots, q_i$; $l = 1, 2, \ldots, q_j$, and $w(t)$ are uncorrelated with each other. Then, similar to scalar measurement case, we can deal with the WMF-QKF. The detailed algorithm is omitted here.

Remark 7. For the case of multiple dimension measurements of each sensor, $H_i(t)$ is assumed to be full row rank. If not, the full-rank decomposition can be implemented. Then the measurement of each sensor can be compressed to a reduced dimension measurement without information loss. Or other compressed algorithms [21, 22] can be used for the multiple dimension measurements of each sensor. Then its each component is quantized and transmitted. Thus, the bandwidth can be saved.

4. Simulation Research

Consider a discrete-time system measured by five sensors:

$$x(t+1) = \begin{bmatrix} 0.9226 & -0.633 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0.5 \\ 0 \\ 0.2 \end{bmatrix} w(t)$$
$$y_i(t) = h_i x(t) + v_i(t), \quad i = 1, 2, 3, \tag{13}$$

where $y_i(t)$ is the measurement signal and $v_i(t)$ is the measurement noise with mean zero and variance $\sigma_{v_i}^2$ and is independent with Gaussian noise $w(t)$ with mean zero and variance σ_w^2. Our goal is to find the WMF-QKF dependent on values (WMF-QKFV) of $\gamma_i(t)$ and WMF-QKF dependent on probabilities (WMF-QKFP) of $\gamma_i(t)$. In the simulation, we set noise variances $\sigma_w^2 = 1$, $\sigma_{v_1}^2 = 1$, $\sigma_{v_2}^2 = 2$, $\sigma_{v_3}^2 = 2.5$, $\sigma_{v_4}^2 = 2.5$, $\sigma_{v_5}^2 = 3$, measurement matrices $h_1 = h_2 = h_3 = [23.738\ 20.287\ 0]$ and $h_4 = h_5 = [0\ 20\ 23]$, the initial values $x(0) = [0\ 0\ 0]^T$ and $P_0 = 0.1I_3$, where I_3 is a 3×3 identity matrix, the bounds $\underline{U}_1 = \underline{U}_2 = \underline{U}_3 = \underline{U}_4 = \underline{U}_5 = -40$ and $\overline{U}_1 = \overline{U}_2 = \overline{U}_3 = \overline{U}_4 = \overline{U}_5 = 40$ for measurements of five sensors, the initial bandwidths $b_1 = b_2 = b_3 = b_4 = b_5 = 1$, and the probabilities $\alpha_1 = 0.5$, $\alpha_2 = 0.7$, $\alpha_3 = 0.8$, $\alpha_4 = 0.8$ and $\alpha_5 = 0.7$ and we take 100 sampling data.

We solve the optimization problem (3) with the bits of the whole bandwidth $B = 12$. We can compute the bandwidths $b_1 = 3$, $b_2 = 3$, $b_3 = 2$, $b_4 = 2$, and $b_5 = 2$. Tracking performance of WMF-QKFV and WMF-QKFP is shown in Figure 2 where bold curves denote the true value, dotted curves denote the estimates of WMF-QKFV, and dashed curves denote the estimates of WMF-QKFP. We see that WMF-QKFV has better accuracy than WMF-QKFP under the same bandwidth constraint. The comparison of mean square errors $\text{MSE}_k = (\sum_{i=1}^{500}(\hat{x}_k^{(i)}(t \mid t) - x_k(t))^2)/500$ by 500 times Monte-Carlo test, $k = 1, 2, 3$, denoting the kth component of the state of all LFs, WMF-QKFV, and WMF-QKFP

(a) The first state component

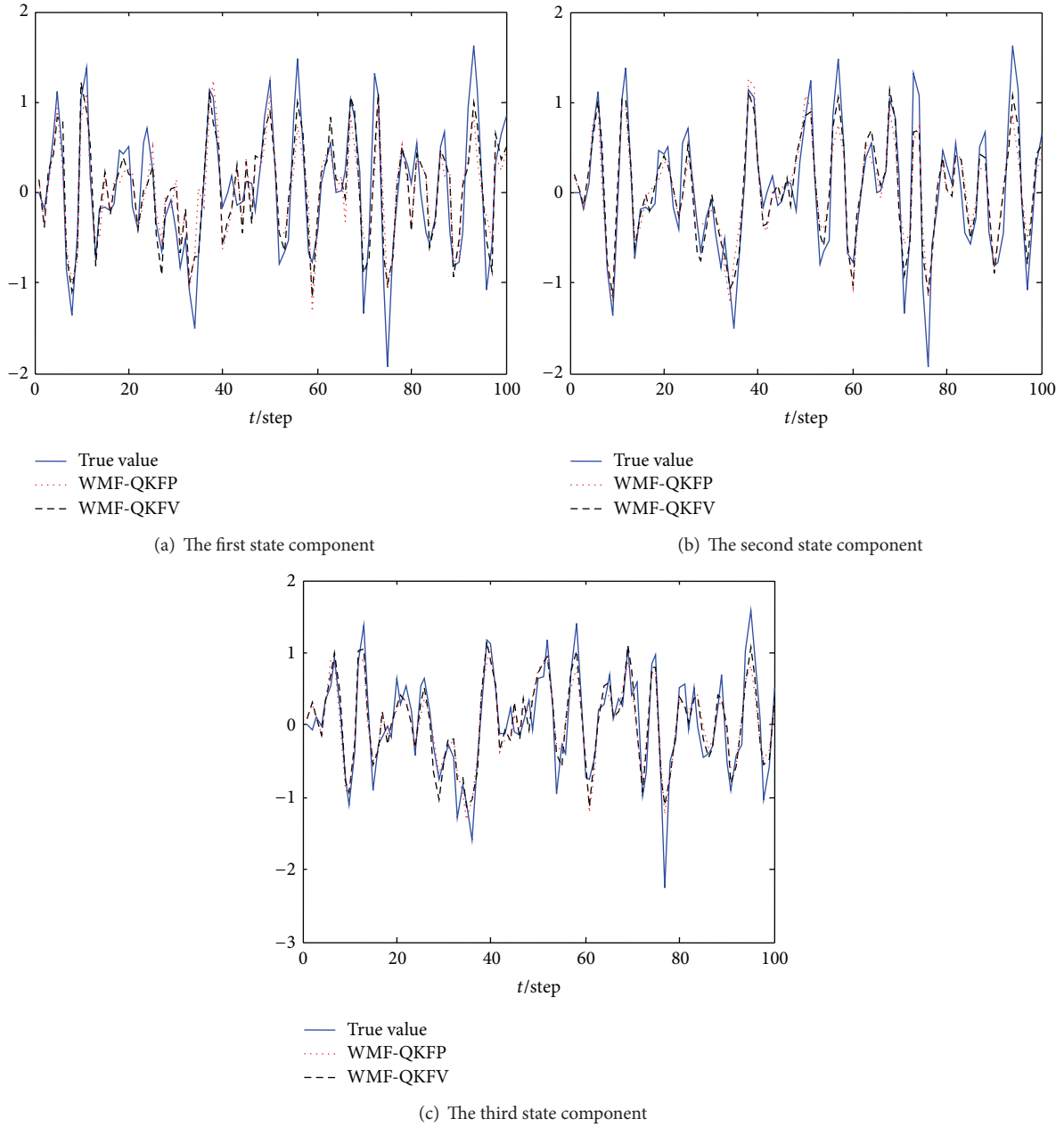(b) The second state component

(c) The third state component

FIGURE 2: Comparison of tracking for WMF-QKFP and WMF-QKFV under whole bandwidth $B = 12$.

is shown in Figure 3. We see that WMF-QKFP and WMF-QKFV have better accuracy than any local filter and WMF-QKFV has better accuracy than WMF-QKFP. All simulations verify the effectiveness of the proposed algorithms.

5. Conclusion

The weighted measurement fusion quantized filtering problem is investigated in a sensor network with bandwidth constraint and imperfect channels of missing measurements. Using the knowledge of whether a measurement is lost at the present time or the probabilities of missing measurements, two weighted measurement fusion quantized Kalman

filters are developed based on the quantized measurements received, respectively. They have the same accuracy as the corresponding centralized fusion estimators and have the reduced computational cost.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

(a) The first state component
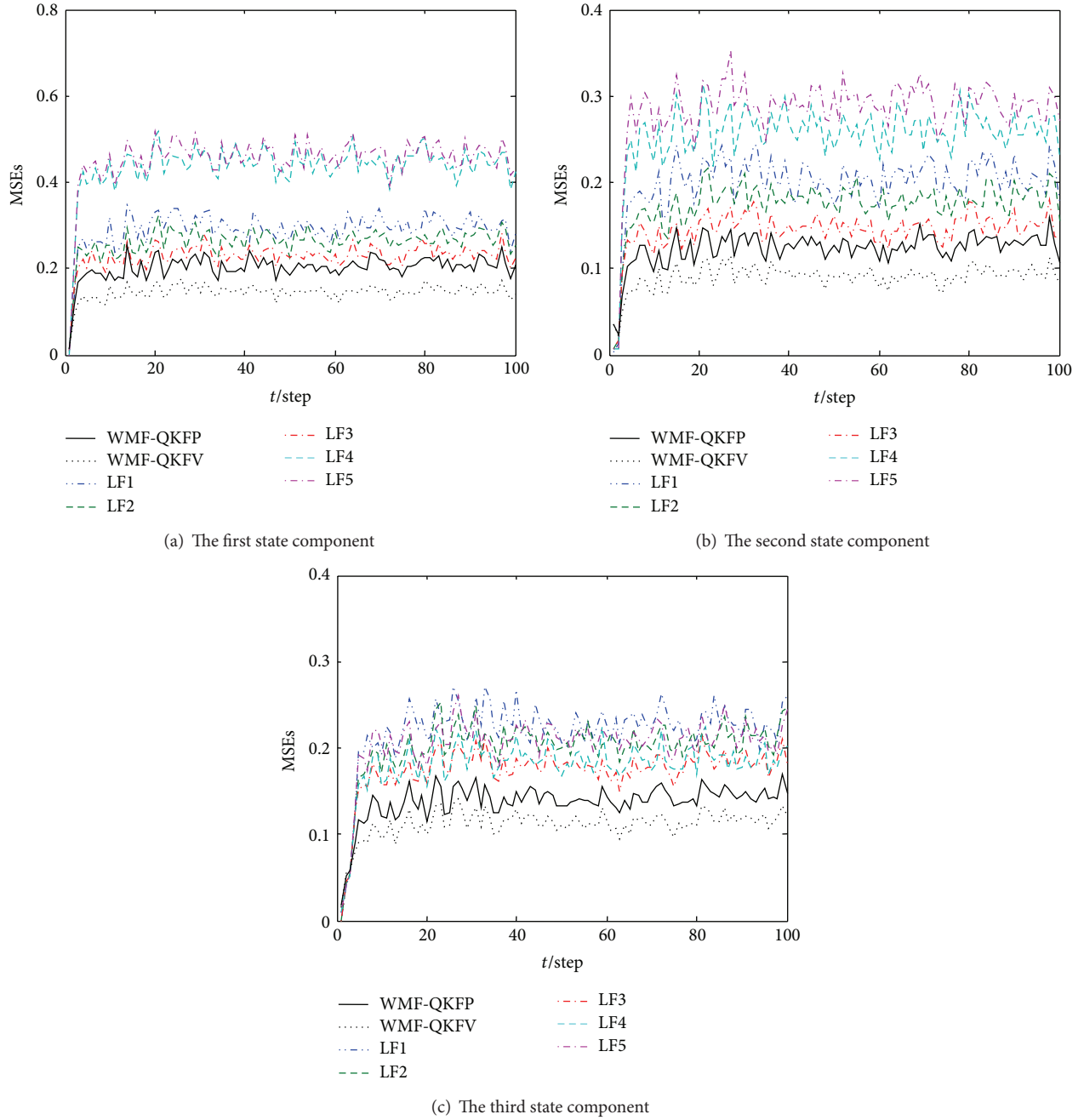

(b) The second state component

(c) The third state component

Figure 3: Comparison of accuracy of WMF-QKFP, WMF-QKFV, and all LFs under whole bandwidth $B = 12$ by 100 times Monte-Carlo test.

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