IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 16, 2018, accepted February 11, 2018, date of publication February 21, 2018, date of current version March 15, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2808337

State Fusion Estimation for Networked Stochastic Hybrid Systems With Asynchronous Sensors and Multiple Packet Dropouts

YANYAN HU[1,2], ZENGWANG JIN[1], AND YAQING WANG[1]
[1]School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing 100083, China
[2]Beijing Engineering Research Center of Industrial Spectrum Imaging, Beijing 100083, China

Corresponding author: Yanyan Hu (huyanyan@ustb.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61773055.

ABSTRACT This paper is concerned with the state fusion estimation problem for a class of stochastic hybrid systems with asynchronous multi-sensors and multiple packet dropouts. The stochastic packet dropouts over communication channels from sensors to the fusion center are formulated as independent Bernoulli sequences. As one of the most cost-effective estimation approach for hybrid systems, the interactive multiple model framework is adopted, where an input mixing step is introduced at the beginning of each filtering cycle. The asynchronous sensor measurements collected at the fusion center are first aligned to the fusion time, and then fused to update the mode-matched filters based on the quasi-recursive form of linear minimum mean square error estimation, where correlations induced by the synchronization process are carefully calculated and the stochastic packet dropouts are taken into account. Finally, the overall estimate is obtained by further fusing the mode-matched estimates with their updated posterior mode probabilities accordingly. The feasibility and effectiveness of the proposed algorithm is illustrated by a numerical simulation.

INDEX TERMS Asynchronous multi-sensor, fusion estimation, networked system, packet dropout, stochastic hybrid system.

I. INTRODUCTION

The past two decades have witnessed the successful applications of networked systems in an extensive range of areas, such as the guidance and navigation, air traffic control, remote diagnostics, and so on. Although the introduction of network has a lot of advantages in practical engineering, it also brings great challenges to the analysis and synthesis of networked systems due to the noisy environment and limited communication capacity of the network [1]. It is well recognized that the existence of network-induced phenomena, such as delays, packet dropouts, and measurement missing, would highly degrade the system performance if not handled properly [2], [3]. Consequently, it is of great importance to consider the network-induced phenomena in the filtering and estimation problems of networked systems.

Packet dropouts may occur via the data transmission in networked systems because of channel congestion, signal degradation, and many other reasons. Actually, the filtering and estimation problem of networked systems with data packet dropouts has attracted considerable research attentions in recent years, and a great number of approaches have been presented in the literature [4]–[9]. In [10], optimal linear filter, predictor and smoother for systems with transmission delays and packet dropouts were proposed based on state augmentation with the convergence of the estimator analyzed. A more general case in networked systems was considered in [11], where one or multiple packets or nothing might be received at the data processing center. An online optimal linear filter in the sense of Linear Minimum Variance (LMV) and an offline suboptimal filter were developed. A recursive networked strong tracking filtering was presented in [5] for a class of nonlinear systems with multiple packet dropouts as well as parameter perturbations and unknown inputs.

For stochastic networked systems measured with multiple sensors, the fusion filtering and estimation problem has also been studied. In [12], centralized fusion estimators in the LMV sense were designed based on the innovation analysis approach. The stability of the proposed fusion estimators was analyzed and a sufficient condition was given for the corresponding steady-state fusion estimators. A centralized fusion strategy based on covariance intersection fusion of local estimates was designed in [13] for networked systems with random packet loss over multiple wireless channels. Based on matrix-weighted fusion approach, a distributed fusion filtering algorithm was proposed in [14] for a class of networked multi-sensor systems, in which transmission delay and packet loss in the communication channel from sensor to local filters were considered. Different from [14], where local estimates were transmitted to the fusion center over a perfect connection, both missing measurements in sensor-to-estimator channels and random delays and packet dropouts in channels from local estimators to the fusion center were taken into account in the proposed distributed fusion estimation algorithm in [15]. For distributed sensor networks with random packet losses, two-phases distributed fusion filters were proposed in [16] with a given topology, where each node was not only a sensor but also a fusion center. A preliminary least-square estimate was firstly obtained at each node using its own measurements and those from its neighbors, and then was further fused with other preliminary estimates collected also from its neighbors using the matrix-weighted fusion approach. Moreover, a networked federated filter was presented in [17] for data-fusion systems with packet losses and variable delays. On the recent progress of estimation, filtering and fusion for networked systems with network-induced phenomena, we refer readers to [18] for more details. However, we want to point out that although fruitful results have been presented, most of those are focused on single model networked systems. In terms of hybrid networked systems consisting of not only continuous state evolutions but also discrete mode transitions, the corresponding results are quite few, and thus, the purpose of this paper is to shorten such a gap.

Motivated by the aforementioned analysis, the state fusion estimation problem for a class of networked stochastic hybrid systems is studied in this paper. Sensor measurements are transmitted to the fusion center via multiple imperfect networks which suffer from stochastic packet dropouts. Moreover, we consider the general case in practice that measurements received at the fusion center are not time-aligned, in other words, they are obtained at different sampling times by multiple asynchronous sensors. This is because sensors in practical applications usually have distinct sampling rates and/or initial sampling times, especially for heterogeneous multiple sensors [19], [20]. A networked state fusion estimation algorithm is developed for a class of stochastic hybrid systems with multiple asynchronous sensors and multiple data packet dropouts based on the IMM framework, one of the most cost-effective algorithms for hybrid system estimation. Similar to IMM, the proposed fusion estimator begins with an input mixing step, and then the mode-matched filters and their mode probabilities are updated with measurements from multiple asynchronous sensors after synchronization. Correlations induced by the synchronizing process are calculated and data packet dropouts over multiple communication channels are taken into account. At last, the overall estimate is obtained by weighting the mode-matched estimates with their mode probabilities accordingly.

The rest of this paper is organized as follows. The stochastic hybrid system considered and the fusion estimation problem are formulated in Section II. In Section III, the proposed networked fusion estimation algorithm is derived. Section IV gives the simulation results to illustrate the effectiveness of the proposed algorithm and the conclusions are drawn in Section V.

II. PROBLEM FORMULATION

Consider a class of stochastic hybrid systems with altogether M candidate modes and the m-th mode is given by the following dynamic equation

$$x(t_j) = \Phi^m(t_j, t_i)x(t_i) + \omega^m(t_j, t_i) \tag{1}$$

where $x \in \mathbb{R}^{d_x}$ is the continuous-valued system state, $\Phi^m(t_j, t_i)$ is the state transition matrix of mode m from t_i to t_j, $\omega^m(t_j, t_i)$ is zero mean white Gaussian noise with covariance $Q^m(t_j, t_i)$. The mode evolution is described by homogeneous Markov chain $\{m(t), t \geq 0\}$ with transition rate matrix Λ.

System (1) is observed by a number of N asynchronous sensors. Since sensors work asynchronously, an individual sensor may have more than one measurement in the k-th fusion time interval $(t_{k-1}, t_k]$. Once for a given sensor, more than one measurement is collected during $(t_{k-1}, t_k]$, only the latest one whose sampling time instant is nearest to t_k is taken into account. Denote the latest measurement of sensor n obtained at time t_k^n as

$$z_k^n = H_k^n x(t_k^n) + v(t_k^n) \tag{2}$$

where $z_k^n \in \mathbb{R}^{d_z^n}$,$t_{k-1} < t_k^n \leq t_k$, $v(t_k^n)$ is zero mean white Gaussian measurement noise with covariance R^n. We also have $E[v(t_k^n)v^T(t_{k'}^{n'})] = R_k^n \delta_{nn'}\delta_{kk'}$, where δ is the Kronecker delta function.

Sensor measurements are transmitted to the fusion filtering center through a communication network, which suffers from random packet dropouts. The observation obtained at the fusion filtering center after data transmission is

$$y_k^n = \theta_k^n z_k^n + \left(1 - \theta_k^n\right) y_{k-1}^n \tag{3}$$

where $\theta_k^n \in \{0, 1\}$ is a Bernoulli stochastic variable, indicating whether measurement z_k^n is received by the fusion center. $\theta_k^n = 0$ means that data packet dropout occurs and in this case the latest measurement received by the fusion center from sensor n is used. The distribution of θ_k^n is

$$Prob\left\{\theta_k^n = 1\right\} = \beta^n \quad Prob\left\{\theta_k^n = 0\right\} = 1 - \beta^n \tag{4}$$

where $\beta^n \in [0, 1]$ is an exactly known scalar, denoting the packet arriving rate of sensor n. We assume that the stochastic data packet dropout θ_k^n are i.i.d., that is

$$E\left\{(\theta_k^n - \beta_k^n)(\theta_{k'}^{n'} - \beta_{k'}^{n'})^T\right\} = [\beta^n - (\beta^n)^2]\delta_{kk'}\delta_{nn'} \tag{5}$$

Also, it is assumed that the system process noise $w(t)$, sensor measurement noise $v(t_k^n)$, the filtering initial state

$x(0)$, and the stochastic data packet dropout θ_k^n are mutually independent.

III. PROPOSED STATE FUSION ESTIMATION ALGORITHM

The purpose of this paper is to find the estimate of system state x at time t_k based on asynchronous measurements $Y^k := \left\{y_{k'}^n, n = 1, \cdots, N, k' = 1, \cdots, k\right\}$ at the fusion center. Using the total probability formula, we have

$$\hat{x}_k = E\{x(t_k)|Y^k\} = \sum_{m=1}^{M} \hat{x}_k^m \mu_k^m \tag{6}$$

and

$$\begin{aligned} P_k &= E\{\left[\hat{x}_k - x(t_k)\right]\left[\hat{x}_k - x(t_k)\right]^T\} \\ &= \sum_{m=1}^{M} [P_k^m + (\hat{x}_k - \hat{x}_k^m)(\hat{x}_k - \hat{x}_k^m)^T]\mu_k^m \end{aligned} \tag{7}$$

where $\hat{x}_k^m = E\{x(t_k)|m(t_k) = m, Y^k\}$ is the state estimate conditioned on mode m with its estimation error covariance $P_k^m = E\{\left[\hat{x}_k^m - x(t_k)\right]\left[\hat{x}_k^m - x(t_k)\right]^T |m(t_k) = m\}$, and $\mu_k^m = Prob\left\{m(t_k) = m|Y^k\right\}$ is the posterior probability that mode m is in effect at time t_k.

The exact calculation of conditional estimate $\hat{x}_k^m$ and its estimation error covariance P_k^m involves all possible mode sequence histories. As time k goes on, the number of mode sequence histories increased exponentially, which makes the optimal approach impractical. To deal with above problem, IMM introduces an input mixing step at the beginning of each filtering cycle based on Gaussian mixing and moment matching [21]. It is this effective input mixing process that makes it possible for IMM to achieve the best compromise between computational complexity and estimation performance. Specifically, the input to each element filter at the current time is re-initialized by mixing the previous estimates of all element filters as

$$\begin{aligned} \check{x}_{k-1}^m &= E\{x(t_{k-1})|m(t_k) = m, Y^{k-1}\} \\ &= \sum_{i=1}^{M} \hat{x}_{k-1}^i \check{\mu}_{k-1}^{i|m} \end{aligned} \tag{8}$$

$$\begin{aligned} \check{P}_{k-1}^m &= Cov\{x(t_{k-1}) - \check{x}_{k-1}^m|m(t_k) = m\} \\ &= Cov\{\tilde{x}_{k-1}^m|m(t_k) = m\} \\ &= \sum_{i=1}^{M} [P_{k-1}^i + (\check{x}_{k-1}^m - \hat{x}_{k-1}^i)(\check{x}_{k-1}^m - \hat{x}_{k-1}^i)^T]\check{\mu}_{k-1}^{i|m} \end{aligned} \tag{9}$$

where $\tilde{x}_{k-1}^m = x(t_{k-1}) - \check{x}_{k-1}^m$, and

$$\begin{aligned} \check{\mu}_{k-1}^{i|m} &= Prob\{m(t_{k-1}) = i|m(t_k) = m, Y^{k-1}\} \\ &= \frac{\pi_{t_k - t_{k-1}}^{i,m} \mu_{k-1}^i}{\mu_{k|k-1}^m} \end{aligned} \tag{10}$$

$$\begin{aligned} \mu_{k|k-1}^m &= Prob\{m(t_k) = m|Y^{k-1}\} \\ &= \sum_{i=1}^{M} \pi_{t_k - t_{k-1}}^{i,m} \mu_{k-1}^i \end{aligned} \tag{11}$$

where $\pi_{t_k - t_{k-1}}^{i,m}$ is the ith row mth column element of $\Pi(t_k - t_{k-1}) = e^{\Lambda(t_k - t_{k-1})}$

Lemma 1: Assume mode m is in effect within time interval $(t_{k-1}, t_k]$. Denote the asynchronous networked measurements received at the fusion center within this time interval as an augmented measurement

$$\bar{y}_k = [(y_k^1)^T, (y_k^2)^T, \cdots, (y_k^N)^T]^T \tag{12}$$

Then $\bar{y}_k$ can be taken as a pseudo-measurement of $x(t_k)$ with its observation equation given by

$$\bar{y}_k = \Theta_k \bar{H}_k^m x(t_k) + \Theta_k \bar{\eta}_k^m + (I - \Theta_k)\bar{y}_{k-1} \tag{13}$$

where

$$\Theta_k = diag\{\theta_k^n I_{d_z^n}\}_{n=1}^N \tag{14}$$

$$\bar{H}_k^m = \left[(H_k^{m,1})^T, (H_k^{m,2})^T, \cdots, (H_k^{m,N})^T\right]^T \tag{15}$$

$$\bar{\eta}_k^m = \left[(\eta_k^{m,1})^T, (\eta_k^{m,2})^T, \cdots, (\eta_k^{m,N})^T\right]^T \tag{16}$$

and for $\forall n \in 1, 2, \cdots, N$,

$$H_k^{m,n} = H_k^n[\Phi^m(t_k, t_k^n)]^{-1} \tag{17}$$

$$\eta_k^{m,n} = v_k^n - H_k^{m,n} w^m(t_k, t_k^n) \tag{18}$$

Meanwhile, $\bar{\eta}_k^m$ is zero mean white Gaussian noise vector with its covariance $\bar{R}_k^m = E\{\bar{\eta}_k^m(\bar{\eta}_k^m)^T\}$ given by

$$\begin{aligned} \bar{R}_k^m(n, n') &= E\{\eta_k^{m,n}(\eta_k^{m,n'})^T\} \\ &= \begin{cases} R_k^n + H_k^{m,n} Q^m(t_k, t_k^n)(H_k^{m,n})^T & n = n' \\ H_k^{m,n} Q^m(t_k, max\{t_k^n, t_k^{n'}\})(H_k^{m,n'})^T & n \neq n' \end{cases} \end{aligned} \tag{19}$$

where $n, n' \in 1, 2, \cdots, N$, and $\bar{R}_k^m(n, n')$ denotes the nth row n'th column submatrix of $\bar{R}_k^m$. In addition, we have

$$\begin{aligned} \Psi_k^m &= E\{w^m(t_k, t_{k-1})(\bar{\eta}_k^m)^T\} \\ &= -[Q^m(t_k, t_k^1)(H_k^{m,1})^T, Q^m(t_k, t_k^2)(H_k^{m,2})^T, \\ &\qquad \cdots, Q^m(t_k, t_k^N)(H_k^{m,N})^T] \end{aligned} \tag{20}$$

Proof 1: Substituting (1) into (2), we have

$$\begin{aligned} z_k^n &= H_k^n[\Phi^m(t_k, t_k^n)]^{-1}\left[x(t_k) - w^m(t_k, t_k^n)\right] + v_k^n \\ &= H_k^n[\Phi^m(t_k, t_k^n)]^{-1} x(t_k) + v_k^n \\ &\quad - H_k^n[\Phi^m(t_k, t_k^n)]^{-1} w^m(t_k, t_k^n) \\ &= H_k^{m,n} x(t_k) + \eta_k^{m,n} \end{aligned} \tag{21}$$

From (3) and (21), it follows

$$y_k^n = \theta_k^n H_k^{m,n} x(t_k) + \theta_k^n \eta_k^{m,n} + (1 - \theta_k^n) y_{k-1}^n \tag{22}$$

Then, (13) can be obtained directly through definition (14)-(16).

In addition, from (18), we know that

$$\begin{aligned} &E\{\eta_k^{m,n}(\eta_k^{m,n})^T\} \\ &= E\{[v_k^n - H_k^{m,n} w^m(t_k, t_k^n)][v_k^n - H_k^{m,n} w^m(t_k, t_k^n)]^T\} \\ &= R_k^n + H_k^{m,n} Q^m(t_k, t_k^n)(H_k^{m,n})^T \end{aligned} \tag{23}$$

and for $n \neq n'$

$$\begin{aligned} &E\{\eta_k^{m,n}(\eta_k^{m,n'})^T\} \\ &\quad = E\{[v_k^n - H_k^{m,n} w^m(t_k, t_k^n)][v_k^{n'} - H_k^{m,n'} w^m(t_k, t_k^{n'})]^T\} \\ &\quad = H_k^{m,n} Q^m(t_k, max\{t_k^n, t_k^{n'}\})(H_k^{m,n'})^T \end{aligned} \quad (24)$$

Meanwhile, we have

$$\begin{aligned} &E\{w^m(t_k, t_{k-1})(\eta_k^{m,n})^T\} \\ &\quad = E\{w^m(t_k, t_{k-1})[v_k^n - H_k^{m,n} w^m(t_k, t_k^n)]^T\} \\ &\quad = -Q^m(t_k, t_k^n)(H_k^{m,n})^T \end{aligned} \quad (25)$$

Consequently, (20) can be obtained directly from (25) and the definition of $\bar{\eta}_k^m$ by (16).

Theorem 1: Given that mode m is in effect within the kth fusion interval $(t_{k-1}, t_k]$, for networked system described by (1)-(3), the predicted state $\hat{x}_{k|k-1}^m = E\{x(t_k)|\not{m}(t_k) = m, Y^{k-1}\}$ and its error covariance $P_{k|k-1}^m = Cov\{x(t_k) - \hat{x}_{k|k-1}^m|\not{m}(t_k) = m\}$ are given by

$$\hat{x}_{k|k-1}^m = \Phi^m(t_k, t_{k-1})\check{x}_{k-1}^m \quad (26)$$

$$P_{k|k-1}^m = \Phi^m(t_k, t_{k-1})\check{P}_{k-1}^m[\Phi^m(t_k, t_{k-1})]^T + Q^m(t_k, t_{k-1}) \quad (27)$$

where $\tilde{x}_{k|k-1}^m = x(t_k) - \hat{x}_{k|k-1}^m$. Meanwhile, by fusing all asynchronous observations $\{y_k^n\}_{n=1}^N$ received at the fusion center, the updated estimate $\hat{x}_k^m$ and its error covariance $P_{k|k-1}^m$ are obtained by

$$\hat{x}_k^m = \hat{x}_{k|k-1}^m + \Gamma_k^m \left(Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\}\right)^{-1} \tilde{y}_{k|k-1}^m \quad (28)$$

$$P_k^m = P_{k|k-1}^m - \Gamma_k^m \left(Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\}\right)^{-1} \Gamma_k^m \quad (29)$$

where

$$\begin{aligned} \tilde{y}_{k|k-1}^m &= \bar{y}_k - E\{\bar{y}_k|\not{m}(t_k) = m, Y^{k-1}\} \\ &= \bar{y}_k - \Xi_k \bar{H}_k^m \hat{x}_{k|k-1}^m - (I - \Xi_k)\bar{y}_{k-1} \end{aligned} \quad (30)$$

$$\Gamma_k^m = P_{k|k-1}^m (\bar{H}_k^m)^T \Xi_k + \Psi_k^m \Xi_k \quad (31)$$

and

$$\Xi_k = E\{\Theta_k\} = diag\{\beta^n I_{d_z^n}\}_{n=1}^N \quad (32)$$

Proof 2: From (1), we have

$$x(t_k) = \Phi^m(t_k, t_{k-1})x(t_{k-1}) + \omega^m(t_k, t_{k-1}) \quad (33)$$

It follows that

$$\begin{aligned} &\hat{x}_{k|k-1}^m \\ &\quad = E\{x(t_k)|\not{m}(t_k) = m, Y^{k-1}\} \\ &\quad = E\{\Phi^m(t_k, t_{k-1})x(t_{k-1}) + \omega^m(t_k, t_{k-1})|\not{m}(t_k) = m, Y^{k-1}\} \\ &\quad = \Phi^m(t_k, t_{k-1})\check{x}_{k-1}^m \end{aligned} \quad (34)$$

and

$$\begin{aligned} &\tilde{x}_{k|k-1}^m \\ &\quad = x(t_k) - \hat{x}_{k|k-1}^m \\ &\quad = \Phi^m(t_k, t_{k-1})x(t_{k-1}) + \omega^m(t_k, t_{k-1}) - \Phi^m(t_k, t_{k-1})\check{x}_{k-1}^m \\ &\quad = \Phi^m(t_k, t_{k-1})[x(t_{k-1}) - \check{x}_{k-1}^m] + \omega^m(t_k, t_{k-1}) \\ &\quad = \Phi^m(t_k, t_{k-1})\tilde{x}_{k-1}^m + \omega^m(t_k, t_{k-1}) \end{aligned} \quad (35)$$

Thus, we have

$$\begin{aligned} P_{k|k-1}^m &= Cov\{\tilde{x}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &= \Phi^m(t_k, t_{k-1})Cov\{\tilde{x}_{k-1}^m|\not{m}(t_k) = m\}[\Phi^m(t_k, t_{k-1})]^T \\ &\quad \times Cov\{\omega^m(t_k, t_{k-1})\} \\ &= \Phi^m(t_k, t_{k-1})\check{P}_{k-1}^m[\Phi^m(t_k, t_{k-1})]^T + Q^m(t_k, t_{k-1}) \end{aligned} \quad (36)$$

Now, using Lemma 1, the fusion filtering problem of networked system described by (1)-(3) can be transformed to the fusion filtering problem of system consisting of discrete-time dynamic equation (33) and the equivalent measurement equation (12). Then, it follows from the results of quasi-recursive form of LMMSE estimation [22], [23] that

$$\begin{aligned} \hat{x}_k^m &= \hat{x}_{k|k-1}^m + Cov\{\tilde{x}_{k|k-1}^m, \tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &\quad \times \left(Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\}\right)^{-1} \tilde{y}_{k|k-1}^m \end{aligned} \quad (37)$$

$$\begin{aligned} P_k^m &= P_{k|k-1}^m - Cov\{\tilde{x}_{k|k-1}^m, \tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &\quad \times (Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\})^{-1} \\ &\quad \times Cov\{\tilde{y}_{k|k-1}^m, \tilde{x}_{k|k-1}^m|\not{m}(t_k) = m\} \end{aligned} \quad (38)$$

and (30) stands obviously from (13), (32) and the definition of $\hat{x}_{k|k-1}^m$.

In addition, from (13), (32), and the definition of $\hat{x}_{k|k-1}^m$, (30) stands obviously. Furthermore, substituting (13) into (30), we have

$$\begin{aligned} \tilde{y}_{k|k-1}^m &= \bar{y}_k - \Xi_k \bar{H}_k^m \hat{x}_{k|k-1}^m - (I - \Xi_k)\bar{y}_{k-1} \\ &= \Theta_k \bar{H}_k^m x(t_k) + \Theta_k \bar{\eta}_k^m + (I - \Theta_k)\bar{y}_{k-1} \\ &\quad - \Xi_k \bar{H}_k^m \hat{x}_{k|k-1}^m - (I - \Xi_k)\bar{y}_{k-1} \\ &= \Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m + (\Theta_k - \Xi_k)\bar{H}_k^m \hat{x}_{k|k-1}^m \\ &\quad - (\Theta_k - \Xi_k)\bar{y}_{k-1} + \Theta_k \bar{\eta}_k^m \end{aligned} \quad (39)$$

Consequently, it follows

$$\begin{aligned} \Gamma_k^m &= Cov\{\tilde{x}_{k|k-1}^m, \tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &= Cov\{\tilde{x}_{k|k-1}^m, \Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m + (\Theta_k - \Xi_k)\bar{H}_k^m \hat{x}_{k|k-1}^m \\ &\quad - (\Theta_k - \Xi_k)\bar{y}_{k-1} + \Theta_k \bar{\eta}_k^m|\not{m}(t_k) = m\} \\ &= Cov\{\tilde{x}_{k|k-1}^m, \Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m + \Theta_k \bar{\eta}_k^m|\not{m}(t_k) = m\} \\ &= P_{k|k-1}^m(\bar{H}_k^m)^T \Xi_k + Cov\{\tilde{x}_{k|k-1}^m, \Theta_k \bar{\eta}_k^m|\not{m}(t_k) = m\} \\ &= P_{k|k-1}^m(\bar{H}_k^m)^T \Xi_k \\ &\quad + Cov\{\Phi^m(t_k, t_{k-1})\tilde{x}_{k-1}^m + \omega^m(t_k, t_{k-1}), \Theta_k \bar{\eta}_k^m\} \\ &= P_{k|k-1}^m(\bar{H}_k^m)^T \Xi_k + Cov\{\omega^m(t_k, t_{k-1}), \Theta_k \bar{\eta}_k^m\} \\ &= P_{k|k-1}^m(\bar{H}_k^m)^T \Xi_k + \Psi_k^m \Xi_k \end{aligned} \quad (40)$$

Theorem 2: $Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\}$ in (28) and (29) is given by

$$\begin{aligned} &Cov\{\tilde{y}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &\quad = Cov\{\Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m|\not{m}(t_k) = m\} \\ &\qquad + Cov\{\Theta_k \bar{\eta}_k^m|\not{m}(t_k) = m\} \\ &\qquad + Cov\{(\Theta_k - \Xi_k)(\bar{H}_k^m \hat{x}_{k|k-1}^m - \bar{y}_{k-1})|\not{m}(t_k) = m\} \\ &\qquad + Cov\{\Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m, \Theta_k \bar{\eta}_k^m|\not{m}(t_k) = m\} \\ &\qquad + Cov\{\Theta_k \bar{\eta}_k^m, \Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m|\not{m}(t_k) = m\} \end{aligned} \quad (41)$$

where

$$
\begin{aligned}
&Cov\{\Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m | \mathfrak{m}(t_k) = m\} \\
&\quad = \Xi_k \bar{H}_k^m P_{k|k-1}^m (\bar{H}_k^m)^T \Xi_k \\
&\qquad + (\Xi_k - \Xi_k^2) diag\{H_k^{m,n} P_{k|k-1}^m (H_k^{m,n})^T\}_{n=1}^N \qquad (42)
\end{aligned}
$$

$$
\begin{aligned}
&Cov\{(\Theta_k - \Xi_k)(\bar{H}_k^m \hat{x}_{k|k-1}^m - \bar{y}_{k-1}) | \mathfrak{m}(t_k) = m\} \\
&\quad = (\Xi_k - \Xi_k^2) \\
&\qquad \times diag\{(H_k^{m,n} \hat{x}_{k|k-1}^m - y_{k-1}^n)(H_k^{m,n} \hat{x}_{k|k-1}^m - y_{k-1}^n)^T\}_{n=1}^N \qquad (43)
\end{aligned}
$$

$$
\begin{aligned}
&Cov\{\Theta_k \bar{\eta}_k^m | \mathfrak{m}(t_k) = m\} \\
&\quad = (\Xi_k - \Xi_k^2) diag\{R_k^n + H_k^{m,n} Q^m(t_k, t_k^n)(H_k^{m,n})^T\}_{n=1}^N \\
&\qquad + \Xi_k \bar{R}_k^m \Xi_k \qquad (44)
\end{aligned}
$$

$$
\begin{aligned}
&Cov\{\Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m, \Theta_k \bar{\eta}_k^m | \mathfrak{m}(t_k) = m\} \\
&\quad = \left\{ Cov\{\Theta_k \bar{\eta}_k^m, \Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m | \mathfrak{m}(t_k) = m\} \right\}^T \\
&\quad = (\Xi_k^2 - \Xi_k) diag\{H_k^{m,n} Q^m(t_k, t_k^n)(H_k^{m,n})^T\}_{n=1}^N \\
&\qquad + \Xi_k \bar{H}_k^m \Psi_k^m \Xi_k \qquad (45)
\end{aligned}
$$

Proof 3: From (39), it follows (46), shown at the bottom of the next page. Based on Lemma 1, and the orthogonality properties of LMMSE, we have (47) and (48), shown at the bottom of the next page. Consequently, (41) stands. Moreover, since $\theta_k^n \in \{0, 1\}$ is a Bernoulli stochastic variable, it follows that $E\{\theta_k^n\} = E\{(\theta_k^n)^2\} = \beta^n$, and then we can have (42), (43), and (44), and it can be obtained that

$$
\begin{aligned}
&Cov\{\Theta_k \bar{H}_k^m \tilde{x}_{k|k-1}^m, \Theta_k \bar{\eta}_k^m | \mathfrak{m}(t_k) = m\} \\
&\quad = Cov\{\Theta_k \bar{H}_k^m [\Phi^m(t_k, t_{k-1}) \tilde{x}_{k-1}^m + \omega^m(t_k, t_{k-1})], \Theta_k \bar{\eta}_k^m\} \\
&\quad = Cov\{\Theta_k \bar{H}_k^m \omega^m(t_k, t_{k-1}), \Theta_k \bar{\eta}_k^m\} \\
&\quad = (\Xi_k^2 - \Xi_k) diag\{H_k^{m,n} Q^m(t_k, t_k^n)(H_k^{m,n})^T\}_{n=1}^N \\
&\qquad + \Xi_k \bar{H}_k^m \Psi_k^m \Xi_k \qquad (50)
\end{aligned}
$$

Accordingly, the mode probabilities are updated by

$$
\begin{aligned}
\mu_k^m &= Prob\left\{\mathfrak{m}(t_k) = m | Y^k\right\} \\
&= \frac{Prob\left\{\mathfrak{m}(t_k) = m | Y^{k-1}\right\} p\left(\bar{y}_k | \mathfrak{m}(t_k) = m, Y^{k-1}\right)}{\sum_{i=1}^{M} Prob\left\{\mathfrak{m}(t_k) = i | Y^{k-1}\right\} p\left(\bar{y}_k | \mathfrak{m}(t_k) = i, Y^{k-1}\right)} \\
&= \frac{\mu_{k|k-1}^m p\left(\bar{y}_k | \mathfrak{m}(t_k) = m, Y^{k-1}\right)}{\sum_{i=1}^{M} \mu_{k|k-1}^i p\left(\bar{y}_k | \mathfrak{m}(t_k) = i, Y^{k-1}\right)} \qquad (51)
\end{aligned}
$$

where $p\left(\bar{y}_k | \mathfrak{m}(t_k) = m, Y^{k-1}\right)$ is given by (49), shown at the bottom of the next page.

Once we get the conditioned estimate $\hat{x}_k^m$, its estimation error covariance P_k^m, and the corresponding mode probability μ_k^m, the combined estimate $\hat{x}_k$ and its error covariance P_k can be directly obtained by (6) and (7) based on the total probability formula, respectively.

IV. SIMULATION RESULTS

In this section, we consider a single target tracking scenario in a 2D horizonal space. The position and velocity of the moving target along X and Y axis are taken as system state, which means the system state vector $x = [X, \dot{X}, Y, \dot{Y}]^T$. Three moving mode are considered: the Coordinated Turn (CT) moving with turning rate $\omega = 0.2\ deg/s$ (named as CT mode 1), CT mode with $\omega = 0.3\ deg/s$ (named as CT mode 2), and the Constant Velocity (CV) mode. We assume that the target starts to move according to CT mode 1 with initial state $[100, 10, 100, 10]^T$, then switches to the CV mode at $t = 20s$, and finally switches to CT mode 2 at $t = 40s$. Consequently, the moving of the target is a typical jump linear system. The simulation ends up at $t = 90s$. The dynamics of the target is given by (1) with parameters given by

CT model:

$$
\Phi(t_j, t_i) = \begin{bmatrix} 1 & \frac{\sin(\omega\tau_{ji})}{\omega} & 0 & \frac{\cos(\omega\tau_{ji}) - 1}{\omega} \\ 0 & \cos(\omega\tau_{ji}) & 0 & -\sin(\omega\tau_{ji}) \\ 0 & \frac{1 - \cos(\omega\tau_{ji})}{\omega} & 1 & \frac{\sin(\omega\tau_{ji})}{\omega} \\ 0 & \sin(\omega\tau_{ji}) & 0 & \cos(\omega\tau_{ji}) \end{bmatrix} \qquad (52)
$$

where turning rate ω takes the value of 0.2 deg/s and 0.3 deg/s in CT mode 1 and CT mode 2, respectively, and $\tau_{ji} = t_j - t_i$. $Q(t_j, t_i)$ is given by (53), shown at the bottom of the next page.

CV model:

$$
\Phi(t_j, t_i) = \begin{bmatrix} 1 & \tau_{ji} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \tau_{ji} \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (54)
$$

$$
Q(t_j, t_i) = \begin{bmatrix} \tau_{ji}^3/3 & \tau_{ji}^2/2 & 0 & 0 \\ \tau_{ji}^2/2 & \tau_{ji} & 0 & 0 \\ 0 & 1 & \tau_{ji}^3/3 & \tau_{ji}^2/2 \\ 0 & 0 & \tau_{ji}^2/2 & \tau_{ji} \end{bmatrix} \times 10^{-2} \qquad (55)
$$

The moving target is observed by three asynchronous sensors with initial sampling instants $t^1 = 0.2s$, $t^2 = 0.3s$, $t^3 = 0.4s$ and sampling periods $T^1 = 0.5s$, $T^2 = 0.5s$, $T^3 = 0.9s$, respectively. The corresponding measurement matrix and measurement noise covariance of these sensors are

$$
H^1 = H^2 = H^3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}
$$

$$
R^1 = R^1 = R^3 = \begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix}
$$

The sensor measurements are transmitted to the fusion center through communication network with random packet dropouts described by (3) and the packet arriving rates in (4) given by $\beta^1 = 0.9$, $\beta^2 = 0.8$, $\beta^3 = 0.8$. respectively. Fig. 1 illustrate the packet dropouts of three asynchronous sensors in one-time realization.

The proposed Networked Asynchronous IMM (NAIMM) fusion estimation algorithm is used to estimate the target state. The fusion filtering period is $T = 1s$ and the initial fusion filtering time instant is $t = 0s$. The initial model probability distribution is [0.8, 0.1, 0.1] and the model transition

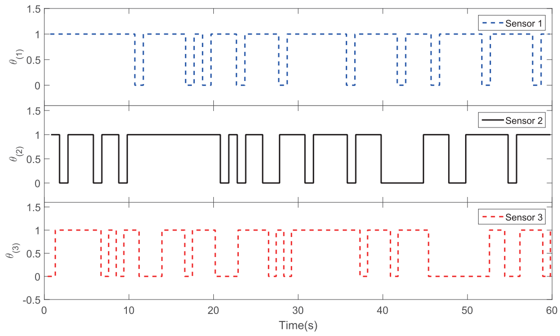


FIGURE 1. Packet dropouts of three asynchronous sensors.

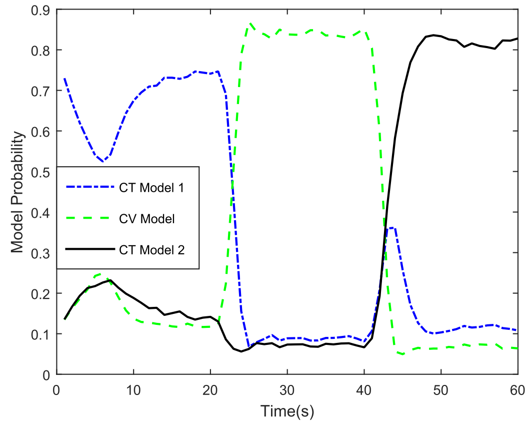


FIGURE 2. Model posterior probabilities of proposed algorithm.

probability matrix is appointed as

$$\Lambda = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.9 & 0.05 \\ 0.05 & 0.05 & 0.9 \end{bmatrix}$$

Fig.2 depicts transition curves of model posterior probability of the proposed NAIMM fusion algorithm. From Fig.2 we can see that the posterior probability of CT model 1 is dominant at the beginning stage since the target starts to move according to CT model 1. After t = 20s, when the moving of the target switches to CV model, the posterior probability of CT model 1 decreases sharply, and that of the CV model increases rapidly and becomes dominant. Meanwhile, the second switch of the target motion pattern from CV model to CT model 2 at t = 40s can also be correctly reflected in the evolution of the posterior model probability curves in Fig.2.

$$\begin{aligned} Cov\{\tilde{y}^m_{k|k-1}|\mathfrak{m}(t_k)=m\} &= Cov\{\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1}+(\Theta_k-\Xi_k)\bar{H}^m_k\hat{x}^m_{k|k-1}-(\Theta_k-\Xi_k)\bar{y}_{k-1}+\Theta_k\bar{\eta}^m_k|\mathfrak{m}(t_k)=m\} \\ &= Cov\{\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1}|\mathfrak{m}(t_k)=m\}+Cov\{(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1})|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{\Theta_k\bar{\eta}^m_k|\mathfrak{m}(t_k)=m\}+Cov\{\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1},\Theta_k\bar{\eta}^m_k|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1},(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1})|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1}),\Theta_k\bar{\eta}^m_k|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1}),\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1}|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{\Theta_k\bar{\eta}^m_k,\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1}|\mathfrak{m}(t_k)=m\} \\ &\quad +Cov\{\Theta_k\bar{\eta}^m_k,(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1})|\mathfrak{m}(t_k)=m\} \end{aligned} \tag{46}$$

$$\begin{aligned} &Cov\{\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1},(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1})|\mathfrak{m}(t_k)=m\} \\ &\quad = \left\{Cov\{(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1}),\Theta_k\bar{H}^m_k\tilde{x}^m_{k|k-1}|\mathfrak{m}(t_k)=m\}\right\}^T=0 \end{aligned} \tag{47}$$

$$\begin{aligned} &Cov\{(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1}),\Theta_k\bar{\eta}^m_k|\mathfrak{m}(t_k)=m\} \\ &\quad = \left\{Cov\{\Theta_k\bar{\eta}^m_k,(\Theta_k-\Xi_k)(\bar{H}^m_k\hat{x}^m_{k|k-1}-\bar{y}_{k-1})|\mathfrak{m}(t_k)=m\}\right\}^T=0 \end{aligned} \tag{48}$$

$$p\left(\bar{y}_k|\mathfrak{m}(t_k)=m,Y^{k-1}\right)=(2\pi)^{-\frac{1}{2}\sum_{n=1}^{N}d^n_z}\left(det\left\{\bar{R}^m_k\right\}\right)^{-\frac{1}{2}}exp\left\{-\frac{1}{2}(\tilde{y}^m_{k|k-1})^T(\bar{R}^m_k)^{-1}\tilde{y}^m_{k|k-1}\right\} \tag{49}$$

$$Q(t_j,t_i)=\begin{bmatrix} \frac{2[\omega\tau_{ji}-\sin(\omega\tau_{ji})]}{\omega^3} & \frac{1-\cos(\omega\tau_{ji})}{\omega^2} & 0 & \frac{\omega\tau_{ji}-\sin(\omega\tau_{ji})}{\omega^2} \\ \frac{1-\cos(\omega\tau_{ji})}{\omega^2} & t_j-t_i & \frac{\sin(\omega\tau_{ji})-\omega\tau_{ji}}{\omega^2} & 0 \\ 0 & \frac{\sin(\omega\tau_{ji})-\omega\tau_{ji}}{\omega^2} & \frac{2[\omega\tau_{ji}-\sin(\omega\tau_{ji})]}{\omega^3} & \frac{1-\cos(\omega\tau_{ji})}{\omega^2} \\ \frac{\omega\tau_{ji}-\sin(\omega\tau_{ji})}{\omega^2} & 0 & \frac{1-\cos(\omega\tau_{ji})}{\omega^2} & t_j-t_i \end{bmatrix} \tag{53}$$

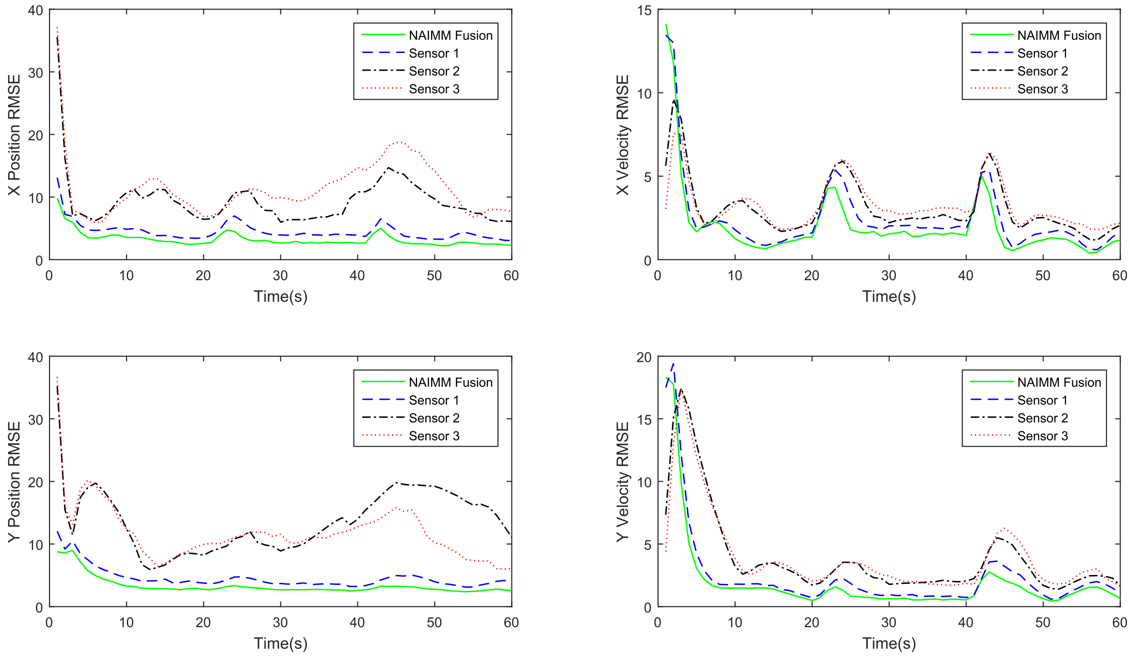


FIGURE 3. Comparison of RMSE cures of position and velocity estimates.

Fig.3 shows the comparison of Root Mean Square Error (RMSE) curves of the proposed NAIMM fusion algorithm and the standard IMM with individual sensors over 500 Monte Carlo runs. The four sub-figures denote the four components of the target state, namely, positions and velocities of the target along X and Y directions, respectively. In these sub-figures, the solid curves denote the proposed NAIMM fusion algorithm, and the dashed, the dash dotted, and the dotted curves denote the standard IMM filterings with individual sensor 1, sensor 2 and sensor 3, respectively. It can be seen from Fig.3 that the proposed NAIMM fusion algorithm has not only the smallest RMSEs during the time a given model is in effect, but also the fastest response to model switches and the smallest model switching errors, which illustrates the feasibility and effectiveness of the proposed fusion algorithm. Besides, the standard IMM with individual sensor 1 has better accuracy than the standard IMM with individual sensor 2 and the standard IMM with individual sensor 3. This is because sensor 1 has smaller sampling period than sensor 3 and higher packet arriving rate than sensor 2. And also this is consistent with our intuition.

V. CONCLUSIONS

A networked state fusion estimation algorithm has been proposed in this paper for a class of stochastic hybrid systems. The proposed algorithm has a similar structure as the standard IMM, but is applicable to asynchronous measurements and takes into account the phenomenon of stochastic packet dropouts of networked systems. After input mixing, the mode-matched estimates are obtained based on the recursive form of LMMSE using the time aligned measurements from multiple asynchronous sensors with noise correlations carefully calculated. The overall estimate is then obtained by weighting the mode-matched estimates with corresponding posterior mode probabilities. Simulation results illustrate the feasibility and effectiveness of the proposed fusion filtering algorithm and verify that it has improved performance than single sensors.

The proposed algorithm can be applicable to networked hybrid systems with multiple asynchronous sensors, such as wireless sensor networks or networked control systems. Further researches can focus on IMM fusion filtering problems for event-triggered networked systems or networked systems with random sensor delays, packet dropouts, and missing observations presented simultaneously.

REFERENCES

[1] N. Saleh, A. Kassem, and A. M. Haidar, "Energy-efficient architecture for wireless sensor networks in healthcare applications," *IEEE Access*, to be published, doi: 10.1109/ACCESS.2018.2789918.

[2] W. M. H. Heemels, A. R. Teel, N. Van de Wouw, and D. Nesic, "Networked control systems with communication constraints: Tradeoffs between transmission intervals, delays and performance," *IEEE Trans. Autom. Control*, vol. 55, no. 8, pp. 1781–1796, Aug. 2010.

[3] R. A. Gupta and M.-Y. Chow, "Networked control system: Overview and research trends," *IEEE Trans. Ind. Electron*, vol. 57, no. 7, pp. 2527–2535, Jul. 2010.

[4] Y. Xia, L. Dai, W. Xie, and Y. Gao, "Network-based data-driven filtering with bounded noises and packet dropouts," *IEEE Trans. Ind. Electron.*, vol. 64, no. 5, pp. 4257–4265, May 2017.

[5] X. He, Z. Wang, X. Wang, and D. H. Zhou, "Networked strong tracking filtering with multiple packet dropouts: Algorithms and applications," *IEEE Trans. Ind. Electron.*, vol. 61, no. 3, pp. 1454–1463, May 2014.

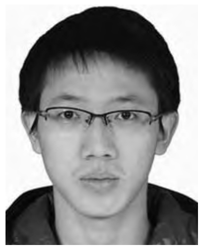
[6] F. Vargas, F. Cid, and A. Maass, "Optimal estimation in feedback control loops with packet dropouts compensation strategies," in *Proc. MED*, Jul. 2017, pp. 993–998.

[7] D. Zhang, Z. Xu, H. R. Karimi, and Q.-G. Wang, "Distributed filtering for switched linear systems with sensor networks in presence of packet dropouts and quantization," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 64, no. 10, pp. 2783–2796, Oct. 2017.

[8] A. Fasano, A. Monteriù, and V. Villani, "A detection-estimation approach to filtering with intermittent observations with generally correlated packet dropouts," in *Proc. CDC*, Dec. 2015, pp. 4356–4361.
[9] W. Ma, J. Duan, W. Man, J. Liang, and B. Chen, "General mixed-norm-based diffusion adaptive filtering algorithm for distributed estimation over network," *IEEE Access*, vol. 5, pp. 1090–1102, 2017.
[10] C. Zhu, Y. Xia, L. Xie, and L. Yan, "Optimal linear estimation for systems with transmission delays and packet dropouts," *IET Signal Process.*, vol. 7, no. 9, pp. 814–823, 2013.
[11] S. Sun and G. Wang, "Modeling and estimation for networked systems with multiple random transmission delays and packet losses," *Syst. Control Lett.*, vol. 73, pp. 6–16, Nov. 2014
[12] J. Ma and S. Sun, "Centralized fusion estimators for multisensor systems with random sensor delays, multiple packet dropouts and uncertain observations," *IEEE Sensors J.*, vol. 13, no. 4, pp. 1228–1235, Apr. 2013.
[13] X. Bian, Y. Xia, L. Yan, and M. Fu, "Data fusion with packet loss," in *Proc. CCC*, Jul. 2014, pp. 7409–7414.
[14] N. Li, S. Sun, and J. Ma, "Multi-sensor distributed fusion filtering for networked systems with different delay and loss rates," *Digit. Signal Process.*, vol. 34, pp. 29–38, Nov. 2014.
[15] B. Chen, W.-A. Zhang, and L. Yu, "Distributed fusion estimation with missing measurements, random transmission delays and packet dropouts," *IEEE Trans. Autom. Control*, vol. 59, no. 7, pp. 1961–1967, Jul. 2014.
[16] R. Caballero-Águila, A. Hermoso-Carazo, and J. Linares-Pérez, "Distributed fusion filters from uncertain measured outputs in sensor networks with random packet losses," *Inf. Fusion*, vol. 34, pp. 70–79, Mar. 2017.
[17] Y. Xia, J. Shang, J. Chen, and G.-P. Liu, "Networked data fusion with packet losses and variable delays," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 39, no. 5, pp. 1107–1120, Oct. 2009.
[18] J. Hu, Z. Wang, D. Chen, and F. E. Alsaadi, "Estimation, filtering and fusion for networked systems with network-induced phenomena: New progress and prospects," *Inf. Fusion*, vol. 31, pp. 65–75, Sep. 2016.
[19] Y. Hu, Z. Jin, S. Qi, and C. Sun, "Estimation fusion for networked systems with multiple asynchronous sensors and stochastic packet dropouts," *J. Franklin Inst.*, vol. 354, no. 1, pp. 145–159, 2017.
[20] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Inf. Fusion*, vol. 14, no. 1, pp. 28–44, 2013.
[21] C. E. Seah and I. Hwang, "Algorithm for performance analysis of the IMM algorithm," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 2, pp. 1114–1124, Apr. 2011.
[22] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation With Applications to Tracking and Navigation: Theory Algorithms and Software*. Hoboken, NJ, USA: Wiley, 2004.
[23] Y. Hu, X. He, L. Zhang, and C. Sun, "IMM fusion estimation with multiple asynchronous sensors," *Signal Process.*, vol. 102, pp. 46–57, Sep. 2014.

YANYAN HU was born in Xianyang, China, in 1981. She received the B.S. degree in information engineering and the M.S. degree in control science and engineering from Xi'an Jiao Tong University, Xi'an, China, in 2003 and 2006, respectively, and the Ph.D. degree in control science and engineering from Tsinghua University, Beijing, China, in 2011.

From 2011 to 2013, she was a Researcher with the IBM Research-China. From 2013 to 2015, she holds a post-doctoral position at the University of Science and Technology Beijing, Beijing, where she is currently a Lecture with the School of Automation and Electrical Engineering. She was a Visiting Scholar with the Department of Electrical Engineering, University of New Orleans, from 2014 to 2015. Her research interest covers filtering and estimation theory, information fusion, fault diagnosis, and fault prediction.



ZENGWANG JIN received the B.S. degree from the School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing, China, in 2013, where he is currently pursuing the Ph.D. degree. His research interest covers state estimation, stochastic hybrid systems and event-triggered systems.

YAQING WANG was born in Taiyuan, China, in 1993. She received the B.S. degree in automation from the Taiyuan University of Science and Technology, Taiyuan, China, in 2016. She is currently pursuing the M.S. degree in control science and engineering with the School of Automation, University of Science and Technology Beijing, Beijing, China. Her current research interests are state estimation and information fusion.