Hindawi
Journal of Control Science and Engineering
Volume 2018, Article ID 5205698, 8 pages
https://doi.org/10.1155/2018/5205698

Research Article

Time-Varying Fault Diagnosis for Asynchronous Multisensor Systems Based on Augmented IMM and Strong Tracking Filtering

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Received 29 June 2017; Accepted 12 November 2017; Published 2 January 2018

Academic Editor: Chunhui Zhao

A fault detection, isolation, and estimation approach is proposed in this paper based on Interactive Multimodel (IMM) fusion filtering and Strong Tracking Filtering (STF) for asynchronous multisensors dynamic systems. Time-varying fault is considered and a candidate fault model is built by augmenting the unknown fault amplitude directly into the system state for each kind of possible fault mode. By doing this, the dilemma of predetermining the fault extent as model design parameters in traditional IMM-based approaches is avoided. After that, the time-varying fault amplitude is estimated based on STF using its strong ability to track abrupt changes and robustness against model uncertainties. Through fusing information from multiple sensors, the performance of fault detection, isolation, and estimation is approved. Finally, a numerical simulation is performed to demonstrate the feasibility and effectiveness of the proposed method.

1. Introduction

In recent years, modern engineering systems have become huge in investment, large in scale, and more and more sophisticated in structure. As a result, faults in these complex systems may lead to enormous losses. Consequently, fault detection and diagnosis (FDD) has attracted more and more attentions as an effective method to reduce the accident risk and enhance the security of systems [1, 2]. The main task of FDD is to perform detection, isolation, and identification of faults in modern systems, that is, to determine whether faults happen, locate the faults, and estimate fault amplitudes [3, 4]. System with faults consists of state evolution in continuous time and parameter or structure changes in discrete time and thus is a typical hybrid system. As the most cost-effective adaptive approach for state estimation of hybrid dynamic systems, Interactive Multimodel (IMM) has been successfully used for FDD of modern engineering systems [5, 6]. In [7], Zhang and Li proposed an integrated framework for FDD of sensor and actuator failures based on IMM. The IMM filtering was performed to model set consisting of the normal model and fault models corresponding to total and partial sensor and/or actuator faults, where extents of partial faults were taken as model parameters and should be predetermined. Ru and Li in [8] proposed an fault diagnosis algorithm by combining IMM and Maximum Likelihood Estimation (MLE), where the fault was detected and located by IMM, and then the fault amplitude was determined by MLE. Zhao et al. in [9] proposed an improved IMM-based FDD, which concentrated on dealing with the mismodeled transition probabilities. A modification operator was used to partition the posterior mode probabilities heuristically and automatically to make the residual error under the true modes approach the white Gaussian process. For aircraft actuator faults, fuzzy logic was utilized in [10] to tune the transition probabilities to make the fault detection process smooth and improve the diagnosis accuracy. Moreover, a novel sensor fault detection, isolation, and identification approach was introduced in [11] for gas turbine engines by combining the proposed multiple hybrid Kalman filters with a modified generalized likelihood ratio method. In addition, IMM-based fault diagnosis techniques have been applied to unmanned aerial vehicles [12], satellites attitude control systems [13], and active fault-tolerant control [14].

On the other hand, with the rapid development of sensor techniques, the number and type of sensors used for system monitoring in modern engineering systems are increased greatly [15, 16]. Consequently, how to effectively integrate the information from multiple sensors to reduce system uncertainties and improve the FDD accuracy is becoming an important research issue [17, 18]. A multisensor fusion and fault detection approach for air traffic surveillance was introduced in [19] based on hybrid estimation. The bias fault and large deviation fault of multilateration and automatic dependence surveillance-broadcast were considered. The proposed method ran two IMM filters in parallel, each for one sensor, and the sensor fault was detected based on the residuals generated by individual filters. The work in [19] is subjected to synchronous sensors. However, in practice, sensors may have different sampling rates, initial sample times, and communication delays, which results in asynchronous measurements [20, 21]. Although asynchronous multisensors have widespread applications, studies aiming at the FDD for asynchronous multisensor systems are relatively much scarce. An actuator fault diagnosis strategy for dynamic systems with multiple asynchronous sensors was presented in [22], where the multiplicative fault factor was considered. An IMM fusion filter was adopted to detect and isolate the fault, while, after that, an augmented Kalman filter was used to estimate the unknown fault factor. Nevertheless, the work in [22] is still limited to time-invariant or slowly time-varying fault because of the sensitivity of Kalman filter to model mismatch.

The aim of this paper is to study the time-varying fault detection, isolation, and estimation problem of stochastic dynamic systems with multiple asynchronous sensors. In existing IMM-based FDD approaches, the unknown fault extent presents as model parameters in candidate fault model and needs to be predetermined in the process of model set design. Meanwhile, since fault extent actually takes value from a continuous interval, several fault models with distinct fault extents for a given kind of fault need to be included in the model set in order to have satisfactory coverage of all possible fault conditions. Different from existing approaches, the proposed FDD strategy in this paper regards the fault amplitude as unknown state variables and augments it directly into the system state to build the candidate fault model. By doing this, for each kind of fault, only one fault model is needed and the dilemma of predetermining the fault extent as model parameters in the model set design process is avoided. Then the asynchronous IMM fusion filtering is performed to the model set consisting of normal model and augmented fault models, and the fault is detected and isolated simultaneously based on the posterior model probabilities. Finally, STF is utilized to jointly estimate the system state and time-varying fault amplitude by fusing all asynchronous measurements from sensors and making use of its strong robustness to model uncertainties.

The rest of this paper is organized as follows. A description of time-varying FDD problem for stochastic dynamic systems with asynchronous sensors is presented in Section 2. The process of model set design is discussed in Section 3. Section 4 illustrates the fault detection and diagnosis based on asynchronous IMM fusion filtering. Section 5 presents the estimation algorithm using STF to estimate the amplitude of the fault. In Section 6, simulation examples are provided to show the effectiveness and feasibility of our method. Finally, conclusions are drawn in Section 7.

2. Problem Formulation

Consider the following continuous-time linear dynamic system:

$$\begin{aligned}\dot{x}(t) = {} & A(t)x(t) + B(t)u(t) + G(t)w(t) \\ & + F(t)e_m f(t),\end{aligned} \tag{1}$$

where $x(t) \in R^{d_x}$ denotes the d_x dimension system state, $u(t) \in R^{d_u}$ denotes the d_u dimension actuator input, and $w(t)$ is the system process noise. $f(t)$ is the scalar fault amplitude signal with e_m denoting the fault direction, where e_m is the mth column of unit matrix I_{d_f} and $m \in \{1, 2, \ldots, d_f\}$. $A(t), B(t), G(t), F(t)$ are correspondingly coefficient matrices with appropriate dimensions. Suppose there are N asynchronous sensors with distinct sample rates and initial sampling times observing system (1).

Let N_k denote all the measurements of the N asynchronous sensors in a time interval $(t_{k-1}, t_k]$. For the fusion time k, we order all of the N_k measurements according to the chronological order to get the measure series $\{y_k^i\}_{i=1}^{N_k}$, where $y_k^i \in R^{d_y^i}$. Let t_k^i be the sampling time of y_k^i; then we have $t_k^i \le t_k^{i+1}$, where the equality holds when y_k^i and y_k^{i+1} are measured at the same time instant. The observation equation is given by

$$y_k^i = H_k^i x\left(t_k^i\right) + v\left(t_k^i\right), \tag{2}$$

where v_k^i is the zero mean Gaussian white noise with the covariance matrix $E\{v_k^i (v_k^j)^T\} = R_k^i \delta_{ij}$, and we assume that v_k^i is uncorrelated with the process noise $w(t)$.

In this paper, time-varying fault $f(t)$ is considered. Actually, in practical applications, the development of fault is relatively slow at the beginning stage and after a certain period of time will become more rapid. Consequently, for fault detection at the initial stage after fault occurs, we assume that it is slowly time-varying and thus it can be regarded as constant in a given fusion interval. Based on above assumption, an augmented IMM is used to simultaneously detect and locate the fault. Then, after the fault is isolated, the STF is performed to jointly estimate the system state and the time-varying fault amplitude $f(t)$, using its strong ability to track abrupt changes and robustness against model uncertainties.

3. Model Set Designs of the Augmented IMM

As we said above, for fault detection and isolation, an augmented IMM is used in this paper. The model set design of the augmented IMM is introduced in this section.

When the mth fault occurs, the system equation is given by (1). At the beginning stage, we assume that, in a small time interval $(t_2, t_1]$, $f(t)$ is time-invariant, where the time interval $(t_2, t_1]$ should be no longer than the fusion interval $T = t_k - t_{k-1}$. Then, from (1), we have the corresponding discrete-time state transition equation

$$\begin{aligned} x(t_2) &= \Phi(t_2, t_1) x(t_1) + u(t_2, t_1) + \xi^m(t_2, t_1) f(t_2) \\ &\quad + w(t_2, t_1), \end{aligned} \tag{3}$$

where $\Phi(t_2, t_1)$ is the state transition matrix from t_1 to t_2, and

$$\begin{aligned} u(t_2, t_1) &= \int_{t_1}^{t_2} \Phi(t_2, \tau) B(\tau) u(\tau) d(\tau) \\ \xi^m(t_2, t_1) &= \int_{t_1}^{t_2} \Phi(t_2, \tau) F(\tau) e_m d(\tau) \\ w(t_2, t_1) &= \int_{t_1}^{t_2} \Phi(t_2, \tau) G(\tau) w(\tau) d(\tau) \\ \Omega(t_2, t_1) &= E\left\{ w(t_2, t_1) w^T(t_2, t_1) \right\} \\ &= \int_{t_1}^{t_2} \Phi(t_2, \tau) G(\tau) Q(\tau) G^T(\tau) \Phi^T(t_2, \tau) d(\tau). \end{aligned} \tag{4}$$

Similarly, for fusion interval $(t_{k-1}, t_k]$, we have

$$\begin{aligned} x(t_k) &= \Phi(t_k, t_{k-1}) x(t_{k-1}) + u(t_k, t_{k-1}) + w(t_k, t_{k-1}) \\ &\quad + \xi^m(t_k, t_{k-1}) f(t_k). \end{aligned} \tag{5}$$

We define

$$\overline{x}_k = \begin{bmatrix} x(t_k) \\ f(t_k) \end{bmatrix} \tag{6}$$

$$\overline{\Phi}_{k-1}^m = \begin{bmatrix} \Phi(t_k, t_{k-1}) & \xi^m(t_k, t_{k-1}) \\ 0 & 1 \end{bmatrix} \tag{7}$$

$$\overline{u}_{k-1}^x = \begin{bmatrix} u(t_k, t_{k-1}) \\ 0 \end{bmatrix} \tag{8}$$

$$\overline{w}_{k-1} = \begin{bmatrix} w(t_k, t_{k-1}) \\ 0 \end{bmatrix}. \tag{9}$$

Then after extending the fault amplitude $f(t_k)$ to the state vector as (6), we have

$$\overline{x}_k = \overline{\Phi}_{k-1}^m \overline{x}_{k-1} + \overline{u}_{k-1}^x + \overline{w}_{k-1}, \tag{10}$$

$$\overline{\Omega}_{k-1} = E\left\{ \overline{w}_{k-1} \overline{w}_{k-1}^T \right\} = \operatorname{diag}\left\{ \Omega(t_k, t_{k-1}), 0 \right\}, \tag{11}$$

where (10) is the fault model corresponding to the mth failure. Let $m = 0$ denote the normal model without fault, while let $m = 1, 2, \ldots, d_f$ be the d_f number of fault models. The IMM model set is composed of the above $d_f + 1$ models.

4. Fault Detection and Isolation Using Augmented IMM

A complete cycle of the IMM-based-FDI scheme is discussed below.

4.1. Input Mixing. Given $Y_k := \{y_k^i\}_{i=1}^{N_k}$, $Y^k := \{Y_l\}_{l=1}^{k}$, then Y^k is the cumulative measurement set of all the asynchronous sensors until the fusion time t_k. Define

$$\begin{aligned} \widehat{x}_k^m &= E\left\{ \overline{x}_k \mid \widetilde{m}(t_k) = m, Y^k \right\} \\ P_k^m &= \operatorname{Cov}\left\{ \overline{x}_k \mid \widetilde{m}(t_k) = m, Y^k \right\} \\ \mu_k^m &= \operatorname{Prob}\left(\widetilde{m}(t_k) = m \mid Y^k \right), \end{aligned} \tag{12}$$

where $\widetilde{m}(t_k) = m$ denotes that the mth model is valid at t_k. The initial value of the mth basic filter is

$$\begin{aligned} \breve{x}_{k-1}^m &= \sum_{i=0}^{d_f} \widehat{x}_{k-1}^i \breve{\mu}_{k-1}^{i|m} \\ \breve{P}_{k-1}^m &= \sum_{i=0}^{d_f} \left[P_{k-1}^i + \left(\breve{x}_{k-1}^m - \widehat{x}_{k-1}^i \right) \left(\breve{x}_{k-1}^m - \widehat{x}_{k-1}^i \right)^T \right] \breve{\mu}_{k-1}^{i|m} \\ \breve{\mu}_{k-1}^{i|m} &= \frac{C_k^m}{\sum_{i=0}^{d_f} C_k^m}, \end{aligned} \tag{13}$$

where $m = 0, 1, \ldots, d_f$, $\lambda^{i,m} = \operatorname{Prob}(\widetilde{m}(t_k) = m \mid \widetilde{m}(t_{k-1}) = i)$ is the transition probability from model i at t_{k-1} to model m at t_k, and $C_k^m = \lambda^{i,m} \mu_{k-1}^i$.

4.2. Model-Conditioned Fusion Filtering. From the state transition equation (3), we have

$$\begin{aligned} x(t_k) &= \Phi(t_k, t_k^i) x(t_k^i) + u(t_k, t_k^i) \\ &\quad + \xi^m(t_k, t_k^i) f(t_k^i) + w(t_k, t_k^i). \end{aligned} \tag{14}$$

Substituting (14) into measurement equation (2), we have

$$\begin{aligned} y_k^i &= H_k^i \Phi^{-1}(t_k, t_k^i) \left[x(t_k) - u(t_k, t_k^i) \right. \\ &\quad \left. - \xi^m(t_k, t_k^i) f(t_k) - w(t_k, t_k^i) \right] + v_k^i = \overline{H}_k^{m,i} \overline{x}_k^m \\ &\quad + u_k^i + \eta_k^i, \end{aligned} \tag{15}$$

where

$$\begin{aligned} \overline{H}_k^{m,i} &= \Pi_k^i \left[I - \xi^m(t_k, t_k^i) \right] \\ \eta_k^i &= v_k^i - \Pi_k^i w(t_k, t_k^i) \\ u_k^i &= -\Pi_k^i u(t_k, t_k^i) \\ \Pi_k^i &= H_k^i \Phi^{-1}(t_k, t_k^i). \end{aligned} \tag{16}$$

Then we define

$$\overline{y}_k = \left[\left(y_k^1\right)^T, \left(y_k^2\right)^T, \ldots, \left(y_k^{N_k}\right)^T\right]^T. \tag{17}$$

Consequently, in the case of mth fault, y_k can be regarded as an equivalent measurement of the augmented system state $\overline{x}_k$ at time t_k, and the equivalent measurement equation is

$$\overline{y}_k = \overline{H}_k^m \overline{x}_k + \overline{u}_k + \overline{\eta}_k, \tag{18}$$

where

$$\overline{H}_k^m = \left[\left(\overline{H}_k^{m,1}\right)^T, \left(\overline{H}_k^{m,2}\right)^T, \ldots, \left(\overline{H}_k^{m,N_k}\right)^T\right]^T. \tag{19}$$

$\overline{u}_k$ and $\overline{\eta}_k$ have the same form as $\overline{H}_k^m$ except for replacing $\overline{H}_k^{m,i}$ with u_k^i and η_k^i, respectively.

Equivalent measurement noise $\overline{\eta}_k$ is a Gaussian white noise with zero mean and covariance matrix $\overline{R}_k = E\{\overline{\eta}_k \overline{\eta}_k^T\} = (\overline{R}_k^{i,j})$, and we further have

$$\overline{R}_k^{i,j} = E\left\{\eta_k^i \left(\eta_k^j\right)^T\right\} = R_k^i \delta_{i,j} + \Pi_k^i \Omega\left(t_k, t_k^i\right)\left(\Pi_k^i\right)^T. \tag{20}$$

At the same time, the equivalent measurement noise $\overline{\eta}_k$ and the process noise $w(t_k, t_{k-1})$ are relevant on account of the common process noise

$$\begin{aligned}\Psi_k &= E\left\{w\left(t_k, t_{k-1}\right)\left(\overline{\eta}_k\right)^T\right\} = -\left[\Omega\left(t_k, t_k^1\right)\right. \\ &\quad \left. \cdot \left(\Pi_k^1\right)^T, \Omega\left(t_k, t_k^2\right)\left(\Pi_k^2\right)^T, \ldots, \Omega\left(t_k, t_k^{N_k}\right)\left(\Pi_k^{N_k}\right)^T\right].\end{aligned} \tag{21}$$

Now for the system composed of the augmented state equation (10) and the equivalent measurement equation (18), the updating equation of the $\widehat{x}_k^m$ and error covariance P_k^m can be obtained as

$$\begin{aligned}\widehat{x}_{k|k-1}^m &= E\left\{\overline{x}_k \mid \widetilde{m}\left(t_k\right) = m, Y^{k-1}\right\} \\ &= \overline{\Phi}_{k-1}^m \breve{x}_{k-1}^m + \overline{u}_{k-1}^x\end{aligned} \tag{22}$$

$$\begin{aligned}P_{k|k-1}^m &= \operatorname{Cov}\left\{\overline{x}_k \mid \widetilde{m}\left(t_k\right) = m, Y^k\right\} \\ &= \overline{\Phi}_{k-1}^m \breve{P}_{k-1}^m \left(\overline{\Phi}_{k-1}^m\right)^T + \overline{\Omega}_{k-1}\end{aligned} \tag{23}$$

$$\widehat{x}_k^m = \widehat{x}_{k|k-1}^m + \Theta_k^m \left(\Xi_k^m\right)^{-1} \widetilde{y}_{k|k-1}^m \tag{24}$$

$$P_k^m = P_{k|k-1}^m - \Theta_k^m \left(\Xi_k^m\right)^{-1} \left(\Theta_k^m\right)^T, \tag{25}$$

where

$$\begin{aligned}\overline{\Psi}_k &= \left[\Psi_k^T, 0_{\sum_{i=1}^{N_k} d_y^i \times 1}\right]^T \\ \Theta_k^m &= P_{k|k-1}^m \left(\overline{H}_k^m\right)^T + \overline{\Psi}_k \\ \Xi_k^m &= \overline{H}_k^m P_{k|k-1}^m \left(\overline{H}_k^m\right)^T + \overline{R}_k + \overline{H}_k^m \overline{\Psi}_k + \left(\overline{H}_k^m \overline{\Psi}_k\right)^T \\ \widetilde{y}_{k|k-1}^m &= \overline{y}_k - \overline{H}_k^m \widehat{x}_{k|k-1}^m - \overline{u}_k.\end{aligned} \tag{26}$$

4.3. Model Probability Update. The model probability of the mth fault should be

$$\begin{aligned}\mu_k^m &= \operatorname{Prob}\left(\widetilde{m}\left(t_k\right) = m \mid Y^k\right) \\ &= \frac{\operatorname{Prob}\left(\widetilde{m}\left(t_k\right) = m \mid Y^{k-1}\right) p\left(\overline{y}_k \mid \widetilde{m}\left(t_k\right) = m, Y^{k-1}\right)}{\sum_{i=0}^{d} \operatorname{Prob}\left(\widetilde{m}\left(t_k\right) = i \mid Y^{k-1}\right) p\left(\overline{y}_k \mid \widetilde{m}\left(t_k\right) = i, Y^{k-1}\right)},\end{aligned} \tag{27}$$

where

$$\begin{aligned}&\operatorname{Prob}\left(\widetilde{m}\left(t_k\right) = m \mid Y^{k-1}\right) = \sum_{i=0}^{d_f} C_k^m \\ &p\left\{\overline{y}_k \mid \widetilde{m}\left(t_k\right) = m, Y^{k-1}\right\} = (2\pi)^{-(1/2)\sum_{i=1}^{N_k} d_y^i} \left|\Xi_k^m\right|^{-1/2} \\ &\quad \cdot \exp\left\{-\frac{1}{2}\left(\widetilde{y}_{k|k-1}^m\right)^T \left(\Xi_k^m\right)^{-1} \widetilde{y}_{k|k-1}^m\right\}.\end{aligned} \tag{28}$$

4.4. Output Combination. Finally from the total probability formula, we have

$$\begin{aligned}\widehat{x}_k &= E\left\{\overline{x}_k \mid Y^k\right\} = \sum_{m=0}^{d_f} \widehat{x}_k^m \mu_k^m \\ P_k &= E\left\{\left(\widehat{x}_k - \overline{x}_k\right)\left(\widehat{x}_k - \overline{x}_k\right)^T\right\} \\ &= \sum_{m=0}^{d_f} \left[P_k^m + \left(\widehat{x}_k - \widehat{x}_k^m\right)\left(\widehat{x}_k - \widehat{x}_k^m\right)^T\right] \mu_k^m.\end{aligned} \tag{29}$$

4.5. Fault Detection and Isolation. Once $\mu_k^i = \max\{\mu_k^m\}_{m=1}^{d_f} > \mu_T$, and for $j = 1, 2, \ldots, L$, we also have $\mu_{k-j}^i > \mu_T$; then the conclusion can be drawn that there is the ith failure in the system, where μ_T is the predetermined detection threshold and L can be regarded as the length of the time window.

Remark 1. The first four steps above constitute the proposed fusion IMM algorithm. The augmented state is estimated under each possible current model through fusing asynchronous measurements from N sensors by Section 4.2, with each filter reinitialed by Section 4.1. The mixed input to each filter is a combination of the previous model-conditioned estimates with mixing probabilities. By this input interaction step, IMM achieves the best compromise between complexity and performance.

5. Fault Amplitude Estimation Based on STF

Once the fault is successfully detected and isolated, the STF could be used to track the development of fault amplitude using its strong ability to track abrupt changes and strong robustness to model mismatch [23, 24]. The augmented estimate $\widehat{x}_k^m$ and its estimation error covariance matrix P_k^m at t_k can be obtained based on STF as (22)–(25) with $\breve{x}_{k-1}^m$ in (22) replaced by $\hat{x}_{k-1}^m$ and the one step predicted error covariance $P_{k|k-1}^m$ given by (23) replaced by

$$P_{k|k-1}^m = \operatorname{diag}\left\{\varphi_k(1), \varphi_k(2), \ldots, \varphi_k(d_x+1)\right\} \times \overline{\Phi}_{k-1}^m P_{k-1}^m \left(\overline{\Phi}_{k-1}^m\right)^T + \overline{\Omega}_{k-1}, \tag{30}$$

where for $i = 1, 2, \ldots, d_x + 1$

$$\begin{aligned} \varphi_k(i) &= \begin{cases} \partial_k(i)\,\varpi_k, & \partial_k(i)\,\varpi_k > 1 \\ 1, & \partial_k(i)\,\varpi_k \le 1 \end{cases} \\ \varpi_k &= \frac{\vartheta_k - \beta \operatorname{tr}\left(\overline{R}_k + \overline{H}_k^m \overline{\Omega}_{k-1} \left(\overline{H}_k^m\right)^T\right)}{\sum_{i=1}^{d_x+1} \partial_k(i)\, W_k(i,i)} \\ W_k &= \overline{\Phi}_{k-1}^m \breve{P}_{k-1}^m \left(\overline{\Phi}_{k-1}^m\right)^T \left(\overline{H}_k^m\right)^T \left(\overline{H}_k^m\right) \\ \vartheta_k &= \begin{cases} \left(\tilde{y}_1^m\right)^T \tilde{y}_1^m, & k = 1 \\ \dfrac{\rho \vartheta_{k-1} + \left(\tilde{y}_{k|k-1}^m\right)^T \tilde{y}_{k|k-1}^m}{1+\rho}, & k \ge 2, \end{cases} \end{aligned} \tag{31}$$

where $0.95 \le \rho < 1$ is the forgetting factor and $\beta \ge 1$ and $\partial_k(i) \ge 1, i = 1, 2, \ldots, d_x + 1$ are the predetermined filter parameters.

6. Simulation Results

In this section, simulation results are provided to verify the proposed algorithm. Consider the dynamic system described by (1) with

$$\begin{aligned} A(t) &= \begin{bmatrix} 0 & 1 & 0 & -0.08 \\ 0 & 0 & 0 & -0.2 \\ 0 & 0.08 & 0 & 1 \\ 0 & 0.2 & 0 & 0 \end{bmatrix} \\ B(t) = G(t) = F(t) &= \begin{bmatrix} 0.5 & 1 & 0 & 0 \\ 0 & 0 & 0.5 & 1 \end{bmatrix}^T, \end{aligned} \tag{32}$$

where the control input is set as $u(t) = \begin{bmatrix} 1 & 1 \end{bmatrix}^T$ and the noise variance $Q(t) = \left[\begin{smallmatrix} 0.01 & 0 \\ 0 & 0.01 \end{smallmatrix}\right]$. When the system works normally, $f(t) = 0$. Suppose the system is observed by three sensors with observation matrices

$$H_{(1)} = H_{(2)} = H_{(3)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{33}$$

and measurement noise covariance matrices

$$R_{(1)} = R_{(2)} = R_{(3)} = \begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix}. \tag{34}$$

The initial sampling instants of the three sensors are $t_{(1)} = 0.1$ s, $t_{(2)} = 0.2$ s, and $t_{(3)} = 0.3$ s, respectively. The sample periods of Sensor 1, Sensor 2, and Sensor 3 are $T_{(1)} = T_{(2)} = 0.6$ s and $T_{(3)} = 0.8$ s. The fusion period of the fusion center is $T = 1$ s. Apparently, these three sensors are asynchronous.

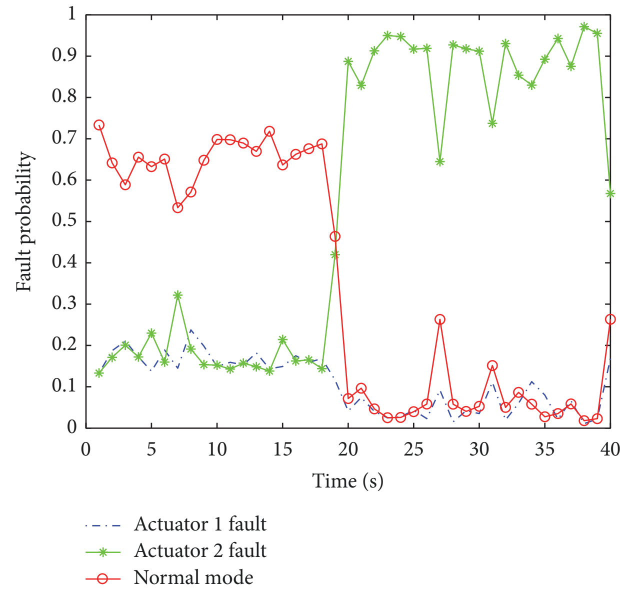

Figure 1: Model probability.

There exist two actuators in this system. Here we assume that Actuator 2 has a time-varying fault which occurs at $\tau_f = 16.5$ s with amplitude $f(t) = 1.5 + 0.1e^{0.04(t-\tau_f)}$. The proposed method is used to diagnose the fault in the system. To perform multimodel fusion filtering, three augmented models are constructed corresponding to three possible situations: normal mode, Actuator 1 fault, and Actuator 2 fault. Figure 1 gives the model probability evolutions during the simulation time in one run. From Figure 1 we can see that the probability of the normal model is dominant before the fault happens. After $t = 16.5$ s when the fault of Actuator 2 occurs, the probability of normal model has a sudden drop, while that of Actuator 2 fault increases rapidly. Therefore, the fault can be correctly detected and located. After that, the augmented IMM is switched to STF to track the variation of the fault amplitude. In the simulation, the value of detection time window L is set to 3, which means we need at least 3 s to conform the fault, which results in the detection delay in Figure 1. Figures 2 and 3 show the root mean-squared errors (RMSE) of the state estimation and the fault amplitude estimation over 500 Monte Carlo runs, respectively. It can be seen from Figures 2 and 3 that both the fused state estimates and the fused fault amplitude estimate have the smallest RMSEs compared to single sensors, which illustrate the effectiveness of the proposed fusion algorithm. Meanwhile, Sensor 3 has worse estimation performance than Sensor 1 and Sensor 2 since it has a lower sampling rate.

7. Conclusion

In this paper, we have presented a new approach for detecting, isolating, and estimating time-varying fault based on IMM and STF for asynchronous multisensor systems. An

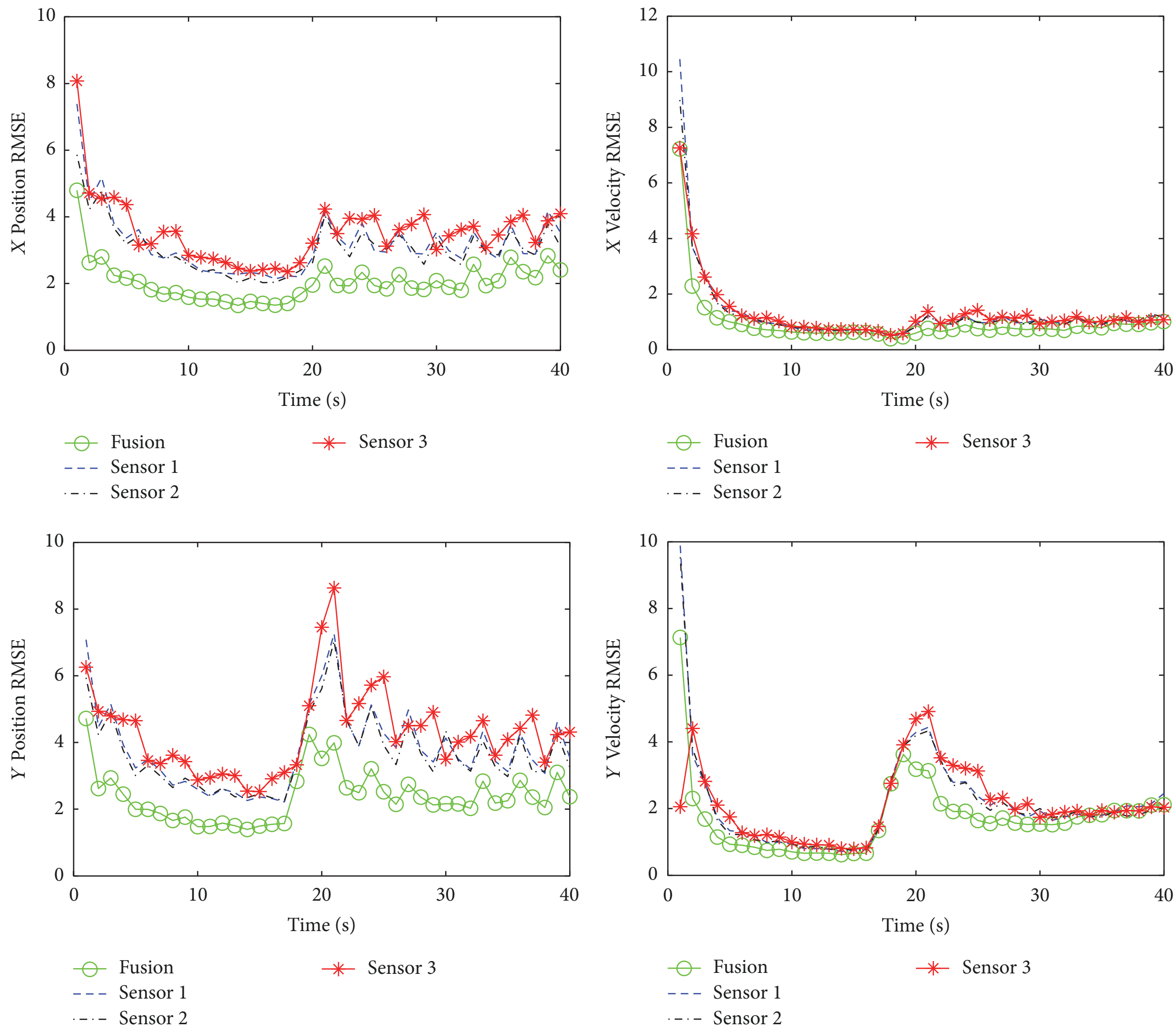

FIGURE 2: RMSE curves of state estimation.

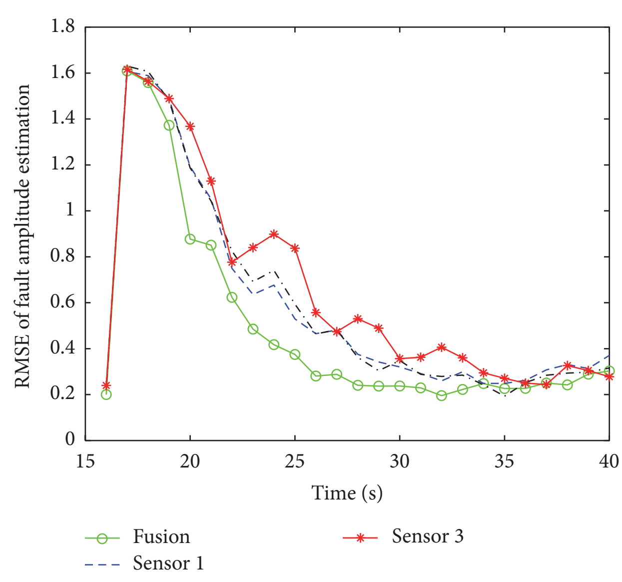

FIGURE 3: RMSE curves of fault amplitude.

augmented IMM has been performed by augmenting the fault amplitude directly into the state vector, and the model probability generated by the augmented IMM has been used to detect and isolate the fault, which is superior to other model-based fault detection methods in that it has a clear detection threshold, while the fault estimation has been achieved based on STF which has good tracking performance for the time-varying fault, even when abrupt changes exist. There are no constraints on the number of the sensors or the initial sample times and sampling rates of multiple sensors. The simulation results demonstrate that the proposed algorithm can detect fault quickly and estimate it accurately. Further works can focus on the fault diagnosis problems on networked systems and systems with state constraints.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China under Grant 61773055, in part by the Fundamental Research Funds for the Central Universities of China with Grant FRF-TP-16-029A3, and in part by the Beijing Key Laboratory of Knowledge Engineering for Materials Science under Grant FRF-BD-16-010A.

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