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Event-Triggered Fault Detection and Diagnosis for Networked Systems With Sensor and Actuator Faults

ZENGWANG JIN[1], YANYAN HU[1,2], CHAO LI[1], AND CHANGYIN SUN[3]

[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
[3]School of Automation, Southeast University, Nanjing 210096, China

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

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ABSTRACT This paper investigates the problem of fault detection, isolation, and estimation for a networked system with actuator and sensor faults. To deal with the bandwidth constraint, an event-triggered scheduling mechanism is utilized to determine whether the sensor observation shall be transmitted to the fault filter according to the importance of information. In this study, two independent Markovian jump chains are introduced to describe the temporal occurrence of sensor fault and the random switching between the normal condition and the faulty ones of the actuator, respectively. To alleviate the compromise between the model number of fault models and computational complexity in the existing interacting multiple models (IMM) approaches, a novel event-triggered fault detection and diagnosis algorithm is proposed based on the augmented IMM framework, where the fault location to be detected is added into the model set and the fault amplitude to be estimated is augmented into the system state. Finally, a Monte Carlo simulation involving tracking a two-dimension moving target is provided to illustrate the effectiveness and efficiency of the proposed method.

INDEX TERMS Event-triggered mechanism, fault diagnosis, stochastic hybrid systems, Markovian jump systems.

I. INTRODUCTION

Over recent years, with the development of technology and science, modern engineering systems are faced with huger investment, larger scale, more sophisticated structure and more complex function [1]–[3]. Reliability consideration, which sometimes possesses a higher priority than performance, is an increasing demand for modern systems to become safe. This requirement extends beyond the normally accepted safety-critical systems of nuclear reactors and aircraft where safety is of paramount importance, to systems such as autonomous vehicles and fast railways where the system availability is vital. Faults or malfunctions from sensors, actuators and plant components may change the system behavior in a drastic manner, ranging from performance degradation to system instability in the worst case. Consequently, it is clear that fault detection and diagnosis (FDD) has been becoming a critical subject in modern control theory and practice to reduce the accident risk and enhance the system security.

Until now, FDD field has received much attention and some interesting results have been achieved, see [4], [5] and the references therein. The main task of FDD is to perform fault detection, isolation and identification if there are faults anywhere in the system. Fault detection is to determine whether the faults happen; Fault isolation is concentrated on pinpointing at the component (sensors, actuators, or plant components) where the faults are located; Fault identification is to estimate the size or severity of fault and the time of its occurrence in some cases. The key point of the traditional observer-based FDD schemes is to construct the residual generator, design the residual evaluation function and the fault threshold, then make a decision whether an alarm of fault is activated by comparing the evaluation function with the prescribed threshold [4], [6]–[8]. For example, [6] studied the observer-based fault detection problem for uncertain

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linear time-variant systems, where the sufficient condition of the existence of a robust fault detection filter was presented via linear matrix inequality techniques. In [7], the fault detector was designed for networked control systems with signal quantization and packet dropouts, where the residual system was proved stochastically stable with a prescribed H_∞ performance level. The fault detection problem for a class of linear quantized feedback systems was explored in [8], where a residual generator was constructed to make a balance between the sensitivity to faults and the robustness against disturbances as well as quantization errors. These results are a little conservative as the FDD problem is converted into a H_∞ filtering problem, which is solved based on the lower and upper bound of the worst case. Besides, the consensus tracking problem for nonlinear multi-agent systems with actuator faults was investigated in [9] based on the adaptive sliding mode method, where the partial loss of effectiveness fault and biased fault were taken into account. [10] proposed a fault-tolerant consensus control strategy for a class of nonaffine multi-agent system, where the proposed neural network-based adaptive consensus protocol had the capacity of rapid response to the actuator faults.

As is known to all, systems with faults consist of continuous-valued sate evolution and the abrupt change of parameter and structure in the system. This class of systems could be described as a typically stochastic hybrid system, which characterizes the random jump of system parameters [11]. As one of the most cost-effective adaptive method for state estimation of stochastic hybrid systems, the interacting multiple model (IMM) approach has a significantly potential role in the solution of the FDD problem of modern engineering systems. In the traditional IMM-based FDD methods [12], [13], the model set is composed of the normal model and fault models associated with potentially partial and total faults from sensors, actuators and plant components, and the fault extent is taken as model parameters to be predetermined. However, performance compromise has to be tolerated to resolve the conflict between the model number of the fault model set and the computational complexity since the fault extent actually allows a continuous-value in the real domain. To overcome this weakness, [14] proposed a combined FDD framework based on variable-structure IMM and maximum likelihood estimation, where a new fault model with estimated fault extent was added to the model set once the fault was detected. Then, the results of [14] were extended in [15] to deal with actuator fault fusion diagnosis for dynamic systems with multiple sensors based on the asynchronous IMM approach, where the fault factor of the partial fault was estimated by using the maximum likelihood estimation algorithm. Besides, a novel fault detection, isolation and estimation method for multi-sensor systems was proposed in [16] based on the augmented IMM structure and the strong tracking filtering approach, where the unknown fault amplitude was directly augmented into the system state to avoid the dilemma of predetermining the fault extent as the model parameters in the traditional IMM approaches.

Note that in the above literature for FDD problem, all sampled data are released under the time-triggered scheduling scheme into the communication network. However, especially for wireless network systems (e.g., unmanned marine vehicles in [17], [18]), bandwidth constraint cannot allow free transmission for a vast of data, which could result in the network-induced phenomenon, such as packet dropout, delay and network congestion, even the system crash. Moreover, from the resource utilization efficiency point of view, measurement outputs of sufficiently small fluctuation are not worth being transmitted to avoid the waste of limited bandwidth resource. Besides, wireless sensors and actuators are usually powered by batteries with limited energy storage, some of which are hard to repair and not even replaceable. To deal with bandwidth limitation and power restriction, event-triggered scheduling scheme becomes a hot research topic and has produced fruitful achievements, see [19]–[23]. Under the event-triggered mechanism, each sensor sends its measurements to the remote processor only when the certain events are activated. Event-triggered mechanism could improve the effectiveness and efficiency of communication bandwidth and power energy via reducing the sensor-to-estimator transmission of data with low importance over wireless sensor networks. For nonlinear networked systems under the event-triggered scheme, [24] designed a polynomial fuzzy fault detection filter based on the residual evaluation function, where the constructed residual system was proved asymptotically stable by the polynomial T-S system approach. [25] was concerned on the problem of fault detection and isolation for event-triggered systems, where the solution of fault diagnosis in the H_∞ performance index was presented by using a Leuberger observer. The problem of event-triggered fault detection filter and controller coordinated design for networked control systems with sensor faults was explored in [26] based on the Wirtinger-based integral inequality method. Most of the current event-triggered FDD approaches are presented in the H_∞ sense, which is a little conservative since it just finds the solution of the worst case. To overcome this conservativeness and improve the accuracy of FDD, the estimation-based event-triggered FDD algorithm in the minimum mean square error sense is one of our motivations to carry out this study, which still remains an unresolved problem.

In this paper, the event-triggered FDD problem is studied for networked control systems with actuator and sensor faults. First, the faulty system is described as a stochastic hybrid system, where two independent Markovian jump chains are introduced to characterize the switchings between the system models (including faulty and normal) and the occurrence of sensor fault, respectively. Then, to improve the efficiency of limited bandwidth resource, the event generator is designed to determine whether the newly sampled measurement output shall be transmitted through the sensor-to-filter channel. A novel estimation-based event-triggered fault filter is proposed based on the augmented IMM framework, where the fault location to be detected is added into the model set and the fault amplitude to be estimated is augmented into the system state. Besides, the statistical knowledge of event-triggered information is utilized to improve the estimation accuracy of fault amplitude and enhance the detect capacity of fault location.

The remainder of this paper is arranged as follows. Section II presents the system description of linear time-invariant systems with actuator and sensor faults, and the event-triggered data scheduling mechanism is designed. An event-triggered fault detection, isolation and estimation algorithm is established based on augmented IMM framework in section III. Section IV illustrates the effectiveness and efficiency of the proposed algorithm by simulation results and conclusions are drawn in section V.

II. PROBLEM FORMULATION AND PRELIMINARIES

A. SYSTEM FORMULATION

In this paper, we consider the state estimation for a class of stochastic linear time-invariant systems along with the possible occurrence of the sensor fault and actuator fault. The output of the target system is measured by the sensors and then evaluated by the event generator before being transmitted through the bandwidth-limited communication network. Assume that the sensor nodes and actuator nodes may encounter fault due to the constraints on actuator fatigue, sensor sensing, temporal failure and so on. The dynamics of stochastic linear time-invariant systems with faults is described as

$$x_{k+1} = Ax_k + Bu_k + Df_k + Gw_k \tag{1}$$

$$y_k = \delta_k H x_k + v_k \tag{2}$$

where k denotes the discrete-time index, $x_k \in \mathbb{R}^{d_x}$ is the continuous-valued system state, u_k is the system input with the dimension d_u, $y_k \in \mathbb{R}^{d_y}$ is the sensor measurement, $w_k \in \mathbb{R}^{d_w}$ and $v_k \in \mathbb{R}^{d_v}$ are mutually independent, additive, white Gaussian noises with zero mean and covariance matrices $Q > 0$ and $R > 0$, respectively. f_k represents the fault vector with the dimension d_f to be detected. δ_k denotes the measurement state, which is determined by the sensor fault. A, B, G, D, H are known matrices with appropriate dimensions.

Due to aging, wear and other reasons, the fault signal f_k inevitably appears in the process of equipment operation. For simplicity, it is assumed in this paper that only one of actuators and process components breaks down at a certain instant and the fault amplitude remains constant or slowly changes. $f_k = e_0$ means that the system works well without any fault, where e_0 is a zero column vector with the dimension d_f. Otherwise, $f_k = e_m f_k^a$ $(1 \leq m \leq d_f)$ denotes the mth fault element is in effect with the fault amplitude f_k^a and others are normal, where e_m is the mth column of unit matrix I_{d_f} denoting the fault direction. The number of candidate operational models including normal and faulty is $d_f + 1$. Let $m_k = m$ $(0 \leq m \leq d_f)$ denote the system model m is in effect at time k, where $m = 0$ is the no fault model and otherwise mth fault occurs. Let the probability vector $\mu_{f,k} = [\mu_{f,k}^0, \cdots, \mu_{f,k}^{d_f}]^T$ indicate the probability of the system matched to each model at time k, i.e., $Pr\{m_k = m\} = \mu_{f,k}^m$ and $\sum_{m=0}^{d_f} \mu_{f,k}^m = 1$. The transition matrix for the evolution of the probability vector $\mu_{f,k}$ is given as Π^f whose elements are defined as $\pi_{nm}^f = Pr\{m_k = m | m_{k-1} = n\}$ for $0 \leq n, m \leq d_f$ with $\sum_{m=0}^{d_f} \pi_{nm}^f = 1$.

Remark 1: the fault signal f_k is introduced to indicate the health condition of actuators and process components, which contains the ovrall information (including type, shape, location and size) of potential faults. If f_k is used to represent the actuator fault for the purpose of fault diagnosis, then it holds true that $D = B$ and $d_f = d_u$, and the final control input is $u_k + f_k$.

The measurement state δ_k, which indicates the sensor fault, is also assumed as a two-state Markov chain independent of m_k and takes values in $\Omega^\delta = \{0, 1\}$, where 1 implies that the sensor can monitor the state of the target without any loss and 0 stands for the occurrence of measurement missing owing to sensor's temporal failure and limited sensing capacity. Let $M_\delta = 2$ be the number of elements in Ω^δ. The transition probability matrix is Π^δ with elements $\pi_{ij}^\delta = Pr(\delta_k = j | \delta_{k-1} = i)$ for all $i, j \in \Omega^\delta$. At time k, the probability distribution of δ_k is denoted as $\mu_{\delta,k} = [\mu_{\delta,k}^1, \mu_{\delta,k}^2]$, where

$$\mu_{\delta,k}^1 + \mu_{\delta,k}^2 = 1, \quad 0 \leq \mu_{\delta,k}^1, \mu_{\delta,k}^2 \leq 1 \tag{3}$$

Taking these fault occurrence into account, the overall system (1) and (2) after the fault occurs could be seen as a typically stochastic hybrid system with continuous state evolution x_k and discrete model transition of m_k and δ_k.

The measurement innovation consists of the part of y_k containing new information but not carried in $y_1, \cdots, y_{k-1}$. For a given mode pair $m_k = m$ and $\delta_k = j$, the measurement innovation $z_k^{j,m} \in \mathbb{R}^{d_z}$ is calculated to reflect the dynamic change of the system state.

$$z_k^{j,m} = y_k - E(y_k | \delta_k = j, m_k = m, I_{k-1}) \tag{4}$$

where I_{k-1} is the history sequence received at the estimator center up to time $k - 1$.

B. EVENT-TRIGGERED DATA SCHEDULING MECHANISM

In the traditional time-triggered scheduling schemes, the observations of the system are sampled and sent periodically with equidistant time intervals completely irrespective of the sampled signals. This is a conservative choice, which leads to excessive occupation of the limited bandwidth resource and the scarce battery power. To improve the resource efficiency, it's of great significance to adopt the event-triggered scheduling mechanism that does not reply on periodicity. In the event-triggered case, the sensor measurements are transmitted through the wireless communication channel only when some predefined conditions dependent of the measurement signal itself are violated. In this section, a novel closed-loop event-triggered mechanism is proposed to effectively save the communication bandwidth and decrease the energy consumption, where the measurement innovation is introduced to trigger certain events.

For the purpose of fault detection, isolation and estimation, the fault amplitude is regarded as the unknown state variable to be estimated and augmented directly into the system state x_k. For a given mode pair $m_k = m$, $\delta_k = j$, the augmented vectors and the corresponding matrices are defined as follows:

$$\bar{x}_k = \begin{bmatrix} x_k \\ f_k^a \end{bmatrix}, \quad \bar{u}_k = \begin{bmatrix} Bu_k \\ 0 \end{bmatrix}, \quad \bar{w}_k = \begin{bmatrix} Gw_k \\ 0 \end{bmatrix}$$
$$\bar{A}_m = \begin{bmatrix} A & De_m \\ 0 & 1 \end{bmatrix}, \quad \bar{H}_j = [jH\ 0]$$
$$\bar{Q}_m = E(\bar{w}_k \bar{w}_k^T) = \text{diag}\{GQG^T, 0\} \tag{5}$$

After extending the fault amplitude f_k^a into the original state vector x_k, then the corresponding discrete-time augmented state transition in (1) and (2) could be modified as

$$\bar{x}_{k+1} = \bar{A}_m \bar{x}_k + \bar{u}_k + \bar{w}_k \tag{6}$$
$$y_k = \bar{H}_j \bar{x}_k + v_k \tag{7}$$

Next, the Mahalanobis transformation is introduced to decouple and normalize the measurement innovation $z_k^{j,m}$ in (4). For a given mode pair $m_k = m$, $\delta_k = j$, the normalized innovation is obtained as

$$\tilde{z}_k^{j,m} = (W_k^{j,m})^T z_k^{j,m} \tag{8}$$

where $W_k^{j,m} \in \mathbb{R}^{d_z \times d_z}$ is given by

$$W_k^{j,m} = U_k^{j,m} (\Lambda_k^{j,m})^{-1/2}$$

and $\Lambda_k^{j,m} = \text{diag}(\lambda_k^{1,j,m}, \cdots, \lambda_k^{d_z,j,m})$ is the diagonal matrix, whose diagonal scalar elements $\lambda_k^{1,j,m}, \cdots, \lambda_k^{d_z,j,m}$ are the eigenvalues of $\bar{H}_j \bar{P}_{k|k-1}^{j,m} \bar{H}_j^T + R > 0$. $U_k^{j,m}$ is a unitary matrix, which is solved below.

Furthermore, the relationship between the diagonal matrix $\Lambda_k^{j,m}$ and the unitary matrix $U_k^{j,m}$ in (8) could satisfy

$$(U_k^{j,m})^T (\bar{H}_j \bar{P}_{k|k-1}^{j,m} \bar{H}_j^T + R) U_k^{j,m} = \Lambda_k^{j,m} \tag{9}$$
$$W_k^{j,m} (W_k^{j,m})^T = (\bar{H}_j \bar{P}_{k|k-1}^{j,m} \bar{H}_j^T + R)^{-1} \tag{10}$$

where $\bar{P}_{k|k-1}^{j,m}$ is the estimation error covariance matrix of the augmented state vector $\bar{x}_k$.

Remark 2: Mhalanobis transformation is widely used to deal with the Mahalanobis distance, which was introduced by P. C. Mahalanobis [27]–[29]. The normalized information through Mhalanobis transformation is unitless and scale-invariant, and takes into account the correlations of the data set.

Remark 3: Through the Mahalanobis transformation (8), the measurement innovation $z_k^{j,m}$ is transformed into the dimensionless and normalized one $\tilde{z}_k^{j,m}$, which is composed of a set of independent and identically distributed principal elements of $z_k^{j,m}$.

After the measurement innovation $\tilde{z}_k^{j,m}$ is normalized by (8), then the sensor node decides whether it will be sent to the estimator for further processing according to the designed event trigger. Let $\gamma_k^{j,m}$ be the decision variable to represent the event occurrence: $\gamma_k^{j,m} = 1$ implies that the normalized innovation $\tilde{z}_k^{j,m}$ is directly sent to the estimator and $\gamma_k^{j,m} = 0$ otherwise. Based on the independent and identical distribution of the normalized innovation, a closed-loop deterministic event-triggered scheme is devised in this paper as

$$\gamma_k^{j,m} = \begin{cases} 1 & \|\tilde{z}_k^{j,m}\|_\infty > \theta^{j,m} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where $\theta^{j,m}$ is a deterministic threshold to decide whether the sensor transmits the explicit data. Note that $\{\|\tilde{z}_k^{j,m}\|_\infty \leq \theta^{j,m}\}$ is equivalent to $\max\{|\tilde{z}_k^{1,j,m}|, \cdots, |\tilde{z}_k^{d_z,j,m}|\} \leq \theta^{j,m}$.

Remark 4: The fault amplitude is taken into account the design of the event-triggered scheduling mechanism in this paper, and the fault location is seen as the system parameter. When the fault signal occurs, the event detector is activated to transit the sensor measurements to rapidly detect, isolate and estimate the amplitude and location of the fault signal.

III. EVENT-TRIGGERED FAULT DETECTION, ISOLATION AND ESTIMATION

System with faults is composed of state evolution in continuous value and parameter or structure changes in discrete value, and thus is a typical hybrid system. As a common technology in hybrid systems, IMM approach is adopted to efficiently and effectively deal with fault detection, isolation and estimation for faulty systems.

The novelty of IMM approach comes from the appropriate timing of hypothesis reduction and performs at a relatively low computation cost. To show the proper timing of hypothesis reduction, a complete cycle from the previous measurement update up to and including the current one is discussed in this section. One filtering cycle is divided into four steps: 1) the model-conditioned re-initialization at the input of filters; 2) the model-conditioned filtering with event-triggered information; 3) the model probability update; 4) the state estimation combination at the output of model-conditioned filters. In addition, compared with the traditional time-triggered IMM approach, the event-triggered one need be redesigned based on the Gaussian assumption, where the implicit information involved in event-triggered scheduling mechanism is further explored in the update stage of the model-conditioned filtering and model probabilities. In this section, a complete cycle of event-triggered IMM fault diagnosis scheme is devised explicitly as follows, including detection, isolation and estimation of fault signals.

Remark 5: For stochastic hybrid systems, the optimal hybrid filter involves all possible mode sequence histories and their associated continuous state evolution. As time k goes on, the number of mode sequence histories grows exponentially, which makes the optimal hybrid filter impractical. To address this exponential growth to the bounded computational complexity, IMM framework introduces an initial interaction step at the beginning of each filtering cycle based on Gaussian mixture and moment matching. It is the effective input mixing process that achieves the best compromise between computational effort and estimation quality.

A. MODEL-CONDITIONED RE-INITIALISATION

Under the event-triggered scheduling mechanism (11), the measurement information set available to the remote estimator at time k is denoted as

$$I(k) = \{\gamma_k^{j,m} z_k^{j,m}\} \bigcup \{\gamma_k^{j,m}\}$$

with $I(-1) \triangleq \emptyset$ and the received information sequence up to time k is $I_k = \{I(1), \cdots, I(k)\}$. Different from the conventional time-triggered case, the received information in event-triggered case is composed of two parts: the decision variable $\gamma_k^{j,m}$ and the coupled information $\gamma_k^{j,m} \times z_k^{j,m}$.

Given the situation that the mode pair $m_k = m$, $\delta_k = j$ is in effect at time k, the model-conditioned priori estimation of the augmented state is defined as

$$\begin{aligned} \hat{x}_{k|k-1}^{j,m} &= E(\bar{x}_k | m_k = m, \delta_k = j, I_{k-1}) \\ \bar{P}_{k|k-1}^{j,m} &= Cov(\bar{x}_k - \hat{x}_{k|k-1}^{j,m}) \end{aligned} \tag{12}$$

and then the corresponding posteriori estimation is

$$\begin{aligned} \hat{x}_{k|k}^{j,m} &= E(\bar{x}_k | m_k = m, \delta_k = j, I_k) \\ \bar{P}_{k|k}^{j,m} &= Cov(\bar{x}_k - \hat{x}_{k|k}^{j,m}) \end{aligned} \tag{13}$$

According to the Markovian property of m_k, the mixing probability of m_k is computed based on the Bayesian theorem

$$\begin{aligned} \pi_{f,k}^{n|m} &= Pr(m_{k-1} = n | m_k = m, I_{k-1}) \\ &= \frac{Pr(m_k = m | m_{k-1} = n, I_{k-1})}{Pr(m_k = m | I_{k-1})} \\ &\quad \times Pr(m_{k-1} = n | I_{k-1}) \\ &= \frac{\pi_{nm}^f \mu_{f,k-1}^n}{\bar{\mu}_{f,k}^m} \end{aligned} \tag{14}$$

where the predicted probability of m_k is obtained by

$$\bar{\mu}_{f,k}^m = Pr(m_k = m | I_{k-1}) = \sum_{n=0}^{d_f} \pi_{nm}^f \mu_{f,k-1}^n \tag{15}$$

Similarly, the mixing probability of δ_k is

$$\begin{aligned} \pi_{\delta,k}^{i|j} &= Pr(\delta_{k-1} = i | \delta_k = j, I_{k-1}) \\ &= \frac{\pi_{ij}^\delta \mu_{\delta,k-1}^i}{\bar{\mu}_{\delta,k}^j} \end{aligned} \tag{16}$$

where the predicted probability of δ_k is

$$\bar{\mu}_{\delta,k}^j = Pr(\delta_k = j | I_{k-1}) = \sum_{i \in \Omega^\delta} \pi_{ij}^\delta \mu_{\delta,k-1}^i \tag{17}$$

Then, due to the independence between the system mode m_k and the measurement state δ_k, the initial input of the basic filter for the mode pair $m_k = m$, $\delta_k = j$ is re-initialized by executing the interaction or mixture of the estimates of all filters at the previous time, e.g.,

$$\begin{aligned} \check{x}_{k-1|k-1}^{j,m} &= \sum_{n=0}^{d_f} \sum_{i \in \Omega^\delta} \hat{x}_{k-1|k-1}^{i,n} \pi_{f,k}^{n|m} \pi_{\delta,k}^{i|j} \\ \check{P}_{k-1|k-1}^{j,m} &= \sum_{n=0}^{d_f} \sum_{i \in \Omega^\delta} \Big[\bar{P}_{k-1|k-1}^{i,n} + (\check{x}_{k-1|k-1}^{j,m} - \hat{x}_{k-1|k-1}^{i,n}) \\ &\quad \times (\check{x}_{k-1|k-1}^{j,m} - \hat{x}_{k-1|k-1}^{i,n})^T \Big] \pi_{f,k}^{n|m} \pi_{\delta,k}^{i|j} \end{aligned} \tag{18}$$

B. MODEL-CONDITIONED FILTERING WITH EVENT-TRIGGERED INFORMATION

According to the dynamics of stochastic hybrid systems, the priori state estimate and the corresponding estimation error covariance matrix matched to the mode pair $m_k = m$, $\delta_k = j$ are obtained as

$$\begin{aligned} \hat{x}_{k|k-1}^{j,m} &= A_m \check{x}_{k-1|k-1}^{j,m} + \bar{u}_k \\ \bar{P}_{k|k-1}^{j,m} &= A_m \check{P}_{k-1|k-1}^{j,m} A_m^T + \bar{Q}_m \end{aligned} \tag{19}$$

The posteriori model-matched estimation of the augmented state depends on whether the event detector is activated to transmit the normalized innovation to the remote filter. To devise the model-conditioned filter with event-triggered scheduling, we consider the following two cases.

1) $\gamma_k^{j,m} = 1$: the event detector is activated to transmit the latest measurement information from the sensor node to the remote estimator. Since the exact point-measurement information is received, the posteriori estimation of the system state is similar to measurement update of classic Kalman filter, e.g.,

$$\begin{aligned} \hat{x}_{k|k}^{j,m} &= \hat{x}_{k|k-1}^{j,m} + K_k^{j,m} \tilde{z}_k^{j,m} \\ \bar{P}_{k|k}^{j,m} &= \bar{P}_{k|k-1}^{j,m} - K_k^{j,m} (K_k^{j,m})^T \end{aligned} \tag{20}$$

where $K_k^{j,m} = \bar{P}_{k|k-1}^{j,m} \bar{H}_j^T W_k^{j,m}$.

2) $\gamma_k^{j,m} = 0$: The processor center does not receive any specific measurement from the sensor node, but is aware of the implicit information extracted from the event-triggered mechanism (11). Then, according to the characteristic of the innovation-based event-triggered mechanism designed in (11), the overall information sequence available to the processor center could be modified as $I_k = \{I_{k-1}\} \bigcup \{\gamma_k^{j,m} = 0\} = \{I_{k-1}, \|\tilde{z}_k^{j,m}\|_\infty \leq \theta^{j,m}\}$.

Based on the standard Gaussian property of the normalized innovation $\tilde{z}_k^{j,m}$, the probability of detector keeping silent could be obtained by solving the integration on the set $\Omega^{j,m} = \{\tilde{z}_k^{j,m} | \|\tilde{z}_k^{j,m}\|_\infty \leq \theta^{j,m}\}$. If $\gamma_k^{j,m} = 0$, then $\tilde{z}_k^{j,m}$ is certainly located in the set $\Omega^{j,m}$, that is to say $Pr(I_k | \tilde{z}_k^{j,m}, m_k = m, \delta_k = j, I_{k-1}) = 1$. Considering the independent and identical distribution of components of the normalized innovation $\tilde{z}_k^{j,m}$, one can yield

$$\begin{aligned} &Pr(I(k)|m_k = m, \delta_k = j, I_{k-1}) \\ &= \int_{\Omega^{j,m}} p(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_{k-1})d\tilde{z}_k^{j,m} \\ &= \prod_{h=1}^{d_z} \int_{\Omega^{j,m}} p(\tilde{z}_k^{h,j,m}|m_k = m, \delta_k = j, I_{k-1})d\tilde{z}_k^{h,j,m} \\ &= [2Q(\theta^{j,m}) - 1]^{d_z} \end{aligned} \tag{21}$$

and

$$Q(\mathrm{x}) = \int_{-\infty}^{\mathrm{x}} \mathcal{N}(\mathrm{y}; 0, 1)d\mathrm{y} \tag{22}$$

where $\mathcal{N}(x; 0, 1)$ is the probability density function of the standard Gaussian variable x with zero mean and variance 1.

Then, given that the mode pair $m_k = m, \delta_k = j$ is in effect at time k, the truncated expectation of the normalized innovation conditioned on the information sequence $I_k = \{I_{k-1}, \|\tilde{z}_k^{j,m}\|_\infty \leq \theta^{j,m}\}$ is derived together with (21)

$$\begin{aligned} &E(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k) \\ &= \int_{\Omega^{j,m}} \tilde{z}_k^{j,m} p(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k)d\tilde{z}_k^{j,m} \\ &= \int_{\Omega^{j,m}} \tilde{z}_k^{j,m} \frac{p(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_{k-1})}{Pr(I_k|m_k = m, \delta_k = j, I_{k-1})} \\ &\quad \times Pr(I_k|\tilde{z}_k^{j,m}, m_k = m, \delta_k = j, I_{k-1})d\tilde{z}_k^{j,m} \\ &= 0 \end{aligned} \tag{23}$$

and the corresponding covariance is also deduced by integration by parts formula as follows

$$\begin{aligned} &Cov(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k) \\ &= \int_{\Omega^{j,m}} \tilde{z}_k^{j,m}(\tilde{z}_k^{j,m})^T p(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k)d\tilde{z}_k^{j,m} \\ &= (1 - \beta(\theta^{j,m}))\mathcal{I}_{d_z} \end{aligned} \tag{24}$$

and

$$\beta(\mathrm{x}) = \frac{2}{\sqrt{2\pi}} \mathrm{x} e^{\frac{-\mathrm{x}^2}{2}} [2Q(\mathrm{x}) - 1]^{-1} \tag{25}$$

where $\mathcal{I}_{d_z}$ is an identity matrix with d_z dimensions.

Consequently, according to the law of total expectation, the posteriori estimation of the augmented state matched to the mode pair $m_k = m, \delta_k = j$ could be achieved along with (24) and (25)

$$\begin{aligned} \hat{x}_{k|k}^{j,m} &= E(\bar{x}_k|m_k = m, \delta_k = j, I_k) \\ &= E\{[\hat{x}_{k|k-1}^{j,m} + K_k^{j,m}\tilde{z}_k^{j,m}]|m_k = m, \delta_k = j, I_k\} \\ &= \hat{x}_{k|k-1}^{j,m} + K_k^{j,m} E\{\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k\} \\ &= \hat{x}_{k|k-1}^{j,m} \end{aligned} \tag{26}$$

Meanwhile, the corresponding estimation error covariance matrix is given based on the principle of orthogonality

$$\begin{aligned} \bar{P}_{k|k}^{j,m} &= Cov(\bar{x}_k - \hat{x}_{k|k}^{j,m}|m_k = m, \delta_k = j, I_k) \\ &= \bar{P}_{k|k-1}^{j,m} - K_k^{j,m}(K_k^{j,m})^T \\ &\quad + K_k^{j,m} Cov(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_k)(K_k^{j,m})^T \\ &= \bar{P}_{k|k-1}^{j,m} - \beta(\theta^{j,m})K_k^{j,m}(K_k^{j,m})^T \end{aligned} \tag{27}$$

Summarizing the above derivations from (20)-(27), the model-matched recursive estimation derivations for the augmented state with event-triggered data scheduling are presented by

$$\begin{aligned} \hat{x}_{k|k}^{j,m} &= \hat{x}_{k|k-1}^{j,m} + \gamma_k^{j,m} K_k^{j,m} \tilde{z}_k^{j,m} \\ \bar{P}_{k|k}^{j,m} &= \bar{P}_{k|k-1}^{j,m} - \left[\gamma_k^{j,m} + (1 - \gamma_k^{j,m})\beta(\theta^{j,m})\right] \bar{P}_{k|k-1}^{j,m} \\ &\quad \times \bar{H}_j^T (\bar{H}_j \bar{P}_{k|k-1}^{j,m} \bar{H}_j^T + R)^{-1} \bar{H}_j \bar{P}_{k|k-1}^{j,m} \end{aligned} \tag{28}$$

C. MODEL PROBABILITY UPDATE

In this section, we will focus on the update of model probabilities according to the received event-triggered information sequence I_k. However, the irregularity and sparsity caused by event-triggered mechanism make it hard. To deal with this challenge, the model probability update is divided into two scenarios in the case of the decision variable $\gamma_k^{j,m} = 1$ or 0.

1) $\gamma_k^{j,m} = 1$: Similar to the classic IMM algorithm, the model probability update step in the proposed event-triggered one could be carried out by using the Bayesian rule. Together with the independence between m_k and δ_k, one can have

$$\begin{aligned} \mu_k^{j,m} &= Pr(m_k = m, \delta_k = j|I_k) \\ &= \frac{p(I(k)|m_k = m, \delta_k = j, I_{k-1})}{p(I(k)|I_{k-1})} \\ &\quad \times Pr(m_k = m, \delta_k = j|I_{k-1}) \\ &= \frac{\mathcal{N}(\tilde{z}_k^{j,m}; 0, \mathcal{I}_{d_z})\mu_{k|k-1}^{j,m}}{\sum_{m=0}^{d_f} \sum_{j \in \Omega^\delta} \mathcal{N}(\tilde{z}_k^{j,m}; 0, \mathcal{I}_{d_z})\mu_{k|k-1}^{j,m}} \end{aligned} \tag{29}$$

where the model-likelihood probability density is computed by

$$\begin{aligned} p(I(k)|m_k = m, \delta_k = j, I_{k-1}) &= p(\tilde{z}_k^{j,m}|m_k = m, \delta_k = j, I_{k-1}) \\ &= \mathcal{N}(\tilde{z}_k^{j,m}; 0, \mathcal{I}_{d_z}) \end{aligned} \tag{30}$$

and the one-step prediction probability of the mode pair $m_k = m, \delta_k = j$ at time k is deduced as

$$\begin{aligned} \mu_{k|k-1}^{j,m} &= Pr(m_k = m, \delta_k = j|I_{k-1}) \\ &= \sum_{n=0}^{d_f} \sum_{i \in \Omega^\delta} \pi_{ij}^\delta \pi_{nm}^f \mu_{k-1}^{i,n} \end{aligned} \tag{31}$$

2) $\gamma_k^{j,m} = 0$: The statistical knowledge of the implicit information involved in the event-triggered conditions is further

utilized to update the model probability. Therefore, the corresponding model probability could be approximated together with (21) and (31)

$$\mu_k^{j,m} = Pr(m_k = m, \delta_k = j|I_k) = \frac{[2Q(\theta^{j,m}) - 1]^{d_z} \mu_{k|k-1}^{j,m}}{\sum_{m=0}^{d_f} \sum_{j\in\Omega^\delta} [2Q(\theta^{j,m}) - 1]^{d_z} \mu_{k|k-1}^{j,m}} \tag{32}$$

Furthermore, the posteriori probability of the system model at $m_k = m$ and $\delta_k = j$ is accumulated, respectively, as

$$\mu_{f,k}^{m} = Pr(m_k = m|I_k) = \sum_{j\in\Omega^\delta} \mu_k^{j,m}$$
$$\mu_{\delta,k}^{j} = P(\delta_k = j|I_k) = \sum_{m=0}^{d_f} \mu_k^{j,m} \tag{33}$$

D. OUTPUT COMBINATION

To avoid the inherent defect of the conventional algorithm called "estimation after decision" in [30], the IMM framework introduces the output combination step by combing all the mode-conditioned estimates matched to different modes weighted by the posteriori probability of the mode pair. Thus, the overall estimation of the augmented state, which embodies the fault extent f_k^a, is generated by

$$\hat{x}_{k|k} = \sum_{m=0}^{d_f} \sum_{j\in\Omega^\delta} \hat{x}_{k|k}^{j,m} \mu_k^{j,m}$$
$$\bar{P}_{k|k} = \sum_{m=0}^{d_f} \sum_{j\in\Omega^\delta} \mu_k^{j,m} [\bar{P}_{k|k}^{j,m} + (\bar{x}_{k|k} - \hat{x}_{k|k}^{j,m})(\bar{x}_{k|k} - \hat{x}_{k|k}^{j,m})^T] \tag{34}$$

Remark 6: Since the fault signal is involved in the augmented state $\bar{x}_k$, the acquisition of the estimate of the augmented state is equivalent to that of the amplitude of the fault signal. Meanwhile, the location of the fault occurrence is detected by the updated model probability $\mu_{f,k}^m$, $(0 \le m \le d_f)$ and $\mu_{\delta,k}^j (j \in \Omega^\delta)$.

E. FAULT DETECTION AND ISOLATION

Model probabilities are utilized as the index of fault modes and normal mode. Once $\mu_{f,k}^{\bar{m}} = \max\{\mu_{f,k}^m\}_{m=1}^{d_f} \ge \bar{\mu}_f$, and for $a = 1, 2, \cdots, L$, we also have $\mu_{f,k-a}^{\bar{m}} \ge \bar{\mu}_f$, then it is indicated that the $\bar{m}$th fault is in effect in the system, where $\bar{\mu}_f \in (0, 1]$ is the predetermined detection threshold of fault signal and L is seen as the length of time window. The fault detection threshold may determine the sensitivity of the proposed algorithm to the faulty mode. Meanwhile, if the probability of the sensor fault $\mu_{\delta,k}^0 \ge \bar{\mu}_\delta$, then we also conclude that the sensor suffers from the failure and malfunction due to various factors, where $\bar{\mu}_\delta$ is the detection threshold of the sensor fault.

IV. SIMULATIONS AND EXPERIMENTS

In this section, a single target tracking scenario in a two-dimension space is given to show the effectiveness and efficiency of the proposed event-triggered IMM fault diagnosis algorithm obtained in the previous section, where the system state $x = [X, \dot{X}, Y, \dot{Y}]$ denotes the position and velocity along the X and Y axes, respectively.

Consider the dynamic system (1) and (2) with the following model parameters:

$$A = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0.5T^2 & 0 \\ T & 0 \\ 0 & 0.5T^2 \\ 0 & T \end{bmatrix}$$
$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad D = G = B$$
$$Q = 0.01 \times \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = 25 \times \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where $T = 1$ is the sampling period and the control input $u_k = [5 \;\; 5]^T$.

In this simulation, there exist two actuators and we assume that the Actuator 1 has encounter the failure at time $\tau_f = 45$s with constant fault extent $f_k^a = 20$. Meanwhile, the measurement missing phenomenon is set to happen at 25s. The sensor fault δ_k is governed by a Markovian jump chain, which has two modes $\{0, 1\}$, and the failure rate $p = 0.1$ and the recovery rate $q = 0.8$. The switching between the normal condition and the faulty ones is also described as a first-order Markovian jump chain. Thus, the transition probability matrices of three system models and the measurement state are, respectively, given by

$$\Pi^f = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.9 & 0.05 \\ 0.05 & 0.05 & 0.9 \end{bmatrix}, \quad \Pi^\delta = \begin{bmatrix} 0.2 & 0.8 \\ 0.1 & 0.9 \end{bmatrix}$$

where the initial model probabilities are $\{\mu_f^0, \mu_f^1, \mu_f^2\} = \{0.7, 0.1, 0.2\}$ and $\{\mu_\delta^0, \mu_\delta^1\} = \{0.5, 0.5\}$. The probability threshold $\bar{\mu}_f = 0.5$ and $\bar{\mu}_\delta = 0.5$

For convenience, the event-triggered threshold $\theta^{j,m}$ is simplified as θ for the mode pair $m_k = m$ and $\delta_k = j$. To analyze the influence of the proposed event-triggered mechanism on the estimation quality and bandwidth occupation, the value of θ is chosen from the set $\theta \in \{0, 0.5, 0.8\}$, where $\theta = 0$ indicates that the event-triggered mechanism is reduced to the time-triggered one and the sensor node could transit the measurement data at a fixed time interval. Then, the proposed event-triggered IMM fault diagnosis algorithm has become the classic IMM one based on the time-triggered scheduling. 500 Monte Carlo runs are carried out in the simulation section and the estimation performance is evaluated in terms of the root square mean error (RMSE).

Fig. 1 shows the posteriori model probability evolution curves calculated the proposed event-triggered fault diagnosis algorithm with $\theta = 0.5$, which are averaged from 500 Monte Carlo runs. As we can see, the probability of the normal

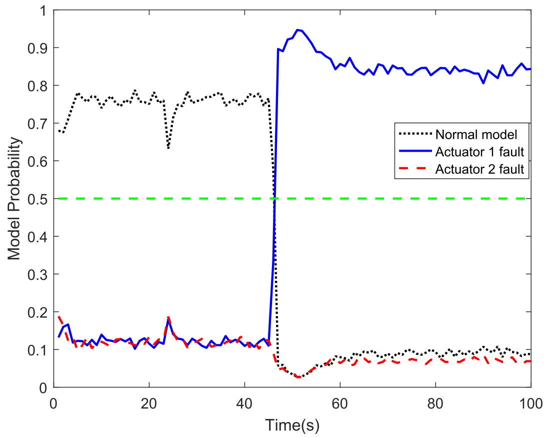

FIGURE 1. Model probability curves obtained by the proposed event-triggered fault diagnosis algorithm with $\theta = 0.5$.

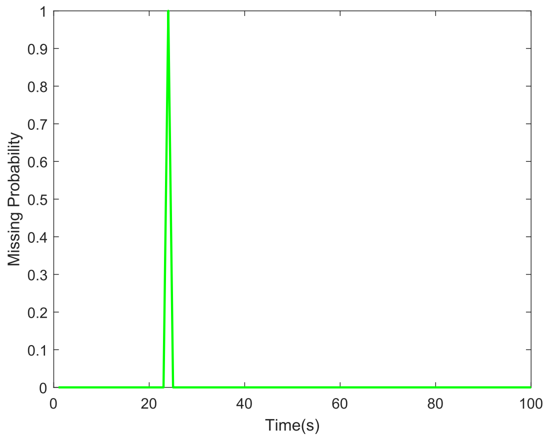

FIGURE 2. The missing probability curve of the measurement data.

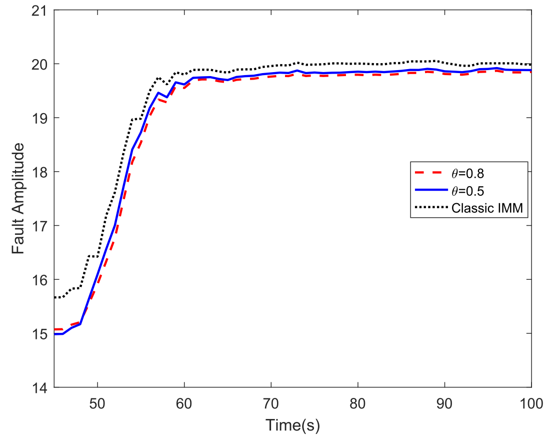

FIGURE 3. The estimated fault amplitude of the proposed event-triggered fault diagnosis algorithm when the fault occurs.

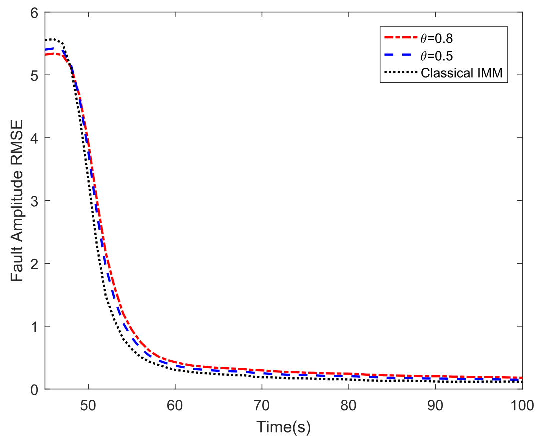

FIGURE 4. The RMSE curves of the fault amplitude of the proposed event-triggered fault diagnosis algorithm when the fault occurs.

model is dominant before the fault occurs. However, once the Actuator 1 fault happens at time $k = 45$s, the model probability of Actuator 1 fault has a sudden increase and quickly exceeds the probability threshold plotted by green dashed line. Meanwhile, the possibility of normal model drops rapidly and the probability of Actuator 2 fault keeps very low described as red dashed line. Thus, the conclusion has been drawn that the fault could be correctly detected and located, which is consistent with the truth.

Fig. 2 shows the updated posteriori probability of the measurement missing (or the sensor fault occurrence) obtained by the proposed algorithm with $\theta = 0.5$. In this simulation example, the occurrence time of measurement missing is set at 25s during 500 Monte Carlo runs. From Fig. 2, it is obvious that the proposed event-triggered fault diagnosis algorithm could precisely distinguish the temporal failure of sensor.

Since the Actuator 1 fault is set to occur at time $k = 45$s, Fig. 3 and Fig. 4 reveal the simulation results of fault signal during the time interval [45s, 100s]. Fig. 3 depicts the fault amplitude estimation of the proposed fault diagnosis algorithm with different event-triggered thresholds in one run. The associated RMSE curves of the fault amplitude estimation over 500 Monte Carlo runs are provided in Fig. 4. From Fig. 3 and Fig. 4, the classic IMM fault diagnosis has lowest estimation error of fault amplitude and fattest response to the fault signal. Moreover, it is observed that the proposed fault diagnosis algorithm could have a more exact estimation accuracy and faster response speed as the event-triggered threshold become smaller.

Fig. 5 and Fig. 6 compares the RMSE curves of the position and velocity estimation along the horizontal direction calculated by the proposed fault diagnosis algorithm with different event-triggered thresholds. From Fig. 5 and Fig. 6, it can be seen that there are two obvious error peaks, where one peak near at 25s is caused by the measurement missing (or the temporal sensor fault) and another peak near at 45s results from the sudden switching between the normal model and Actuator 1 fault. As indicated in Fig. 5 and Fig. 6, we can observe that the proposed event-triggered fault diagnosis algorithm can also track the true trajectory with a low estimation error in the RMSE sense. In addition, the estimation performance of the proposed algorithm becomes better with the decrease of even-triggered threshold, even in peak positions. Compared with classic IMM fault diagnosis

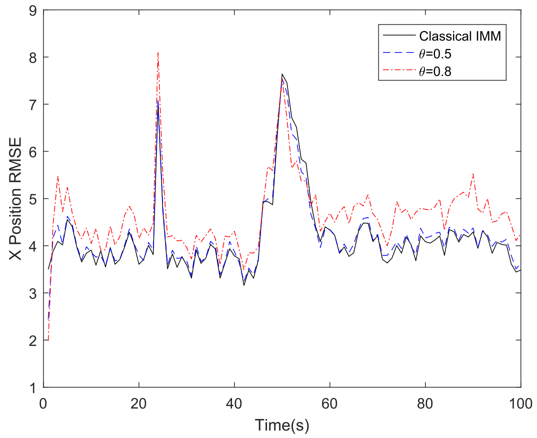

FIGURE 5. Comparison of RMSE in position along the horizontal direction with 500 Monte Carlo runs.

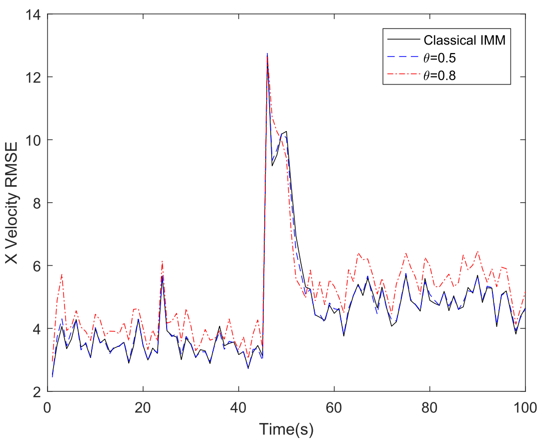

FIGURE 6. Comparison of RMSE in velocity along the horizontal direction with 500 Monte Carlo runs.

algorithm with full-rate communication, although there is a slight deterioration of the estimation performance, our proposed algorithm can save 5% and 10% communication bandwidth for $\theta = 0.5$ and 0.8, respectively. From the above discussions, it is verified that the proposed event-triggered fault diagnosis algorithm could dramatically improve the efficiency of limited bandwidth by not transmitting a large amount of data of less importance while satisfying the desirable estimation quality.

V. CONCLUSION

In this paper, we have proposed a novel FDD algorithm based on the augmented IMM framework for event-triggered stochastic systems with actuator and sensor faults. The transitions of the system models (including normal and faulty) and the measurement missing are characterized by two independent first-order Markovian jump chains, respectively. Compared with time-triggered IMM fault diagnosis methods, the proposed event-triggered approach could substantially enhance the efficiency of bandwidth resources and battery power while guaranteeing the satisfactory ability of fault diagnosis and estimation performance. Our proposed method has been performed to detect and isolate the fault by model probabilities, and estimate the fault extent by augmenting the fault extent into the state vector. To avoid additional computational burden, the statistical knowledge implicit in the designed event-triggered mechanism is utilized to update model probability, and estimate fault severity when the detector keeps silent. Meanwhile, the simulation results demonstrate that it owns a fast response speed to the actuator fault signal and can exactly detect the temporal sensor fault. The proposed method has a simply recursive framework of fault diagnosis for the real-time monitoring of various applications over wireless sensor networks, such as battlefield surveillance and intelligent transportation. Future works could focus on the event-triggered fusion diagnosis problem for multi-sensor networked systems, e.g., the sensor sampling frequency is arbitrary and asynchronous. Besides, the proposed event-triggered FDD algorithm will be applied into the practical systems to show the practical usefulness, especially for unmanned marine vehicles.

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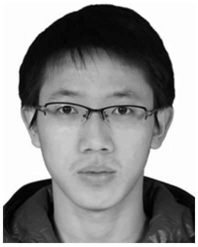

ZENGWANG JIN received the bachelor's degree from the School of Automation and Electrical Engineering, University of Science and Technology Beijing, in 2013, where he is currently pursuing the Ph.D. degree in control science and engineering. He was a visiting Ph.D. student with the Department of Mechanical, Industrial and Aerospace Engineering (MIAE), Concordia University, Montreal, QC, Canada, from 2015 to 2017. His research interests include fault diagnosis, state estimation, stochastic hybrid systems, and event-triggered systems.

YANYAN HU received the B.S. and M.S. degrees from the School of the Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an, China, in 2003 and 2006, respectively, and the Ph.D. degree from the Department of Automation, Tsinghua University, in 2011. She is currently an Associate Professor with the School of Automation and Electrical Engineering, University of Science and Technology Beijing. Her research interests currently focus on fault diagnosis, stochastic hybrid systems, and estimation and information fusion.

CHAO LI received the bachelor's degree from the School of Electronic Information Engineering, Hebei University, in 2017. He is currently pursuing the master's degree with the School of Automation and Electrical Engineering, University of Science and Technology Beijing. His research interests include state estimation, fault diagnosis, and remaining useful life prediction.

CHANGYIN SUN received the bachelor's degree from the College of Mathematics, Sichuan University, Chengdu, China, in 1996, and the M.S. and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 2001 and 2003, respectively. He is currently a Distinguished Professor with the School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing, China, and the School of Automation, Southeast University. His current research interests include intelligent control, flight control, pattern recognition, and optimal theory. He is currently an Associate Editor of the IEEE Transactions on Neural Networks and Learning Systems.