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Robust detection of intermittent sensor faults in stochastic LTV systems

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ABSTRACT

This paper addresses the detection problem of intermittent sensor faults for linear time-varying (LTV) systems with stochastic uncertainties. A robust filter is proposed which has advantages of zero mean and minimum state estimation error covariance. Then a corresponding residual generator is constructed and the quantitative influence of sensor faults on it is analyzed. Next, we design the evaluation function and detection threshold to achieve intermittent fault detection (IFD). Besides, the detectability of sensor faults is also provided. Finally, a simulation study is carried out to illustrate the effectiveness and applicability of our proposed method.

1. Introduction

With the higher demand of efficiency, reliability and safety of modern automation systems, the fault diagnosis technique has played a more important role than ever before. It has thus aroused world-wide attention and fruitful research results have been reported on it [1–3]. However, most of them only concentrate on permanent faults. By comparison, the research on intermittent faults is relatively scarce. The intermittent fault (IF) can be seen as a kind of special non-permanent fault that lasts for a limited period of time and then disappears without any external corrective operations [4]. Besides, it often recurs due to the same cause. The IF is very common in a lot of engineering systems, such as electronics systems [5], aerospace systems [6], electric power systems [7], etc. Therefore, it is of significant importance to carry out research on intermittent fault diagnosis.

Up to present, there have only been some initial results on intermittent fault diagnosis in the literature. They can be roughly categorized into two general classes: offline testing approaches and online diagnosis approaches. The main idea of offline testing approaches is to inject certain fault-related inputs and repeatedly test whether there is discrepancy between the expected and actual outputs [8–10]. Meanwhile, the main idea of online diagnosis approaches is to utilize the priori system information and online measurement information to achieve real-time diagnosis.

Due to the advantages of economics and flexibility, the online diagnosis approaches have attracted more research attention in the past decades. They can be broadly divided into two categories: model-based approaches, and data-driven approaches. The model-based approaches mainly include: causal model based methods [11–13], discrete event system model based methods [14–16], and analytical model based methods [17–20]. While the data-driven approaches primarily contain: decision forest based methods [21], and signal analysis based methods [22–24].

On the other hand, the increasing automation of modern engineering systems have made sensors become more crucial. Any failures of sensors have the potential to cause a series of severe problems and even calamitous consequences. As a result, broad attention has been paid to sensor fault diagnosis techniques from both academia and industry. And some sensor fault diagnosis methods have been developed including model-based approaches [25–33] and data-driven approaches [34–36]. The model-based approaches can be further classified into parameter estimation

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based methods [25,26], parity space based methods [27–29], and state estimation based methods [30–33].

Summarizing the above discussion, it can be concluded that although the intermittent fault diagnosis problem has stirred some initial research interest, the corresponding robust detection problem of intermittent additive and multiplicative sensor faults in stochastic linear time-varying (LTV) systems has yet not been adequately investigated. The task of this problem is challengeable which requires to detect both the occurrence and disappearance of additive and multiplicative faults. It will be more difficult to study this problem in the presence of stochastic uncertainties caused by parameter perturbations in engineering systems.

It should be noted that most available results on robust fault detection require to obtain exact information of uncertainty structure beforehand, and are within the framework of norm index. However, sometimes it may be difficult to get this information and there is still a need of a different robust detection method based on statistical information rather than structural information. In view of the above facts, we are motivated to develop a novel robust intermittent fault detection (IFD) method for both additive and multiplicative sensor faults. We will fully mine the statistical information and analyze the fault influence to overcome the difficulties of this problem. The main contributions of this paper can be summarized as follows: *1) a robust intermittent sensor fault method is proposed based on our robust filter; 2) the quantitative relationship between the sensor faults and residual is presented; 3) the detectability of both additive and multiplicative sensor faults is given.*

The rest of this paper is organized as follows. In Section 2, the robust intermittent sensor fault detection problem is formulated with some assumptions. In Section 3, the robust IFD method is developed and analyzed in details. Simulation results are provided and discussed in Section 4. In the end, some concluding remarks are given in Section 5.

Notations. In this paper, the notations are fairly standard except where otherwise stated. $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ denote the n dimensional Euclidean space and the set of all $n \times m$ real matrices, respectively. $\mathbf{0}_{n\times m}$ represents the null matrix with n rows and m columns (0 at all entries), and $\mathbf{I}_{n\times n}$ represents the identity matrix with n rows and n columns (1 at the (i, i)th entry and 0 elsewhere). $\mathcal{S}(m,n)$ denotes the set $\{m, m+1, \ldots, n\}, (m \in \mathbb{Z}, n \in \mathbb{Z}, m \le n)$. Given a matrix $\mathbf{Y} = [y_{ij}] \in \mathbb{R}^{n\times m}$, row$\{\mathbf{Y}, i\}$ denotes the vector $\begin{bmatrix} y_{i1} & y_{i2} & \cdots & y_{im}\end{bmatrix}^T$. Given a set $\mathcal{V} = \{n_1, n_2, \ldots, n_m\}, (n_1 \le n_2 \le \cdots \le n_m)$, $\text{col}_{i\in\mathcal{V}}\{\mathbf{Y}_i\}$ and $\text{diag}_{i\in\mathcal{V}}\{\mathbf{Y}_i\}$ denote the block-column matrix $\begin{bmatrix}\mathbf{Y}_{n_1}{}^T & \mathbf{Y}_{n_2}{}^T & \cdots & \mathbf{Y}_{n_m}{}^T\end{bmatrix}^T$ and block-diagonal matrix $\text{diag}\{\mathbf{Y}_{n_1}, \mathbf{Y}_{n_2}, \cdots \mathbf{Y}_{n_m}\}$, respectively. $\mathbb{E}\{\mathbf{Y}\}$ is the mathematical expectation of a stochastic variable $\mathbf{Y}$. $\mathrm{p}_{\text{row}}(\mathbf{Y})$, $\boldsymbol{\mu}_\mathbf{Y}$, $\boldsymbol{\Sigma}_\mathbf{Y}$ represent $\text{col}_{i\in\mathcal{S}(1,n)}\{\text{row}\{\mathbf{Y}, i\}\}$, $\mathbb{E}\{\mathbf{Y}\}$, $\mathbb{E}\{\mathrm{p}_{\text{row}}(\mathbf{Y})\mathrm{p}_{\text{row}}(\mathbf{Y})^T\}$, respectively. If the dimensions of matrices are not explicitly stated, they are assumed to be compatible for algebraic operations.

2. Problem formulation and preliminaries

Consider a class of stochastic LTV systems with both additive and multiplicative sensor faults:

$$\mathbf{x}(k+1) = (\mathbf{A}_c(k) + \mathbf{A}_\delta(k))\mathbf{x}(k) + (\mathbf{B}_c(k) + \mathbf{B}_\delta(k))\mathbf{u}(k) + \mathbf{w}(k), \tag{1}$$

$$\mathbf{y}(k) = \left(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}} + \mathbf{F}_m(k)\right)(\mathbf{C}_c(k) + \mathbf{C}_\delta(k))\mathbf{x}(k) + \mathbf{v}(k) + \mathbf{f}_a(k), \tag{2}$$

where $\mathbf{x}(k) \in \mathbb{R}^{n_\mathbf{x}}$ is the system state, $\mathbf{u}(k) \in \mathbb{R}^{n_\mathbf{u}}$ is the control input, and $\mathbf{y}(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the measurement output. $\mathbf{w}(k) \in \mathbb{R}^{n_\mathbf{x}}$ is the process noise, and $\mathbf{v}(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the measurement noise. $\mathbf{A}_c(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{x}}$, $\mathbf{B}_c(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{u}}$, $\mathbf{C}_c(k) \in \mathbb{R}^{n_\mathbf{y}\times n_\mathbf{x}}$ are known deterministic parameters, and $\mathbf{A}_\delta(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{x}}$, $\mathbf{B}_\delta(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{u}}$, $\mathbf{C}_\delta(k) \in \mathbb{R}^{n_\mathbf{y}\times n_\mathbf{x}}$ are unknown stochastic parameter uncertainties, which are used to describe parameter perturbations. $\mathbf{f}_a(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the additive fault, and $\mathbf{F}_m(k) \in \mathbb{R}^{n_\mathbf{y}\times n_\mathbf{y}}$ is the multiplicative fault, i.e.,

$$\mathbf{F}_m(k) = \begin{bmatrix} f_m(k)^{(1)} & 0 & \cdots & 0 \\ 0 & f_m(k)^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & f_m(k)^{(n_\mathbf{y})} \end{bmatrix}. \tag{3}$$

The intermittent faults are in the following forms:

$$\mathbf{f}_a(k) = \sum_{i=1}^{\infty} \mathbf{f}_{a,i}\Big(\Gamma(k - k_{a,o,i}) - \Gamma\big(k - k_{a,d,i}\big)\Big), \tag{4}$$

$$\mathbf{F}_m(k) = \sum_{i=1}^{\infty} \mathbf{F}_{m,i}\Big(\Gamma(k - k_{m,o,i}) - \Gamma\big(k - k_{m,d,i}\big)\Big), \tag{5}$$

where $\mathbf{f}_{a,i}$ is the ith additive fault profile, and $\mathbf{F}_{m,i}$ is the ith multiplicative fault profile. $k_{a,o,i}$, $k_{a,d,i}$ are occurrence and disappearance time of additive fault, and $k_{m,o,i}$, $k_{m,d,i}$ are occurrence and disappearance time of multiplicative fault. $\Gamma(\cdot)$ is the unit step function. The summation function describes the general case that the intermittent faults may occur and disappear recurrently. The occurrence and disappearance time of the intermittent faults are completely unknown. The above system is called normal system if both the additive and multiplicative faults are identically equal to zero. Otherwise, it is called faulty system.

Thanks to the diagonal structure of multiplicative fault, we can rewrite (2) as

$$\mathbf{y}(\mathbf{k}) = (\mathbf{C_c}(\mathbf{k}) + \mathbf{C}_\delta(\mathbf{k}))\mathbf{x}(\mathbf{k}) + \mathbf{v}(\mathbf{k}) + \mathbf{E_F}(\mathbf{k})\mathbf{f_m}(\mathbf{k}) + \mathbf{f_a}(\mathbf{k}), \tag{6}$$

where

$$\mathbf{E_F}(k) = \text{diag}_{i\in\mathcal{S}(1,n_\mathbf{y})}\{\text{row}\{(\mathbf{C}_c(k) + \mathbf{C}_\delta(k))\mathbf{x}(k), i\}\}, \tag{7}$$

$$\mathbf{f}_m(k) = \begin{bmatrix} f_m(k)^{(1)} & f_m(k)^{(2)} & \cdots & f_m(k)^{(n_\mathbf{y})}\end{bmatrix}^T. \tag{8}$$

The following assumptions are made throughout this paper.

Assumption 1. The initial state $\mathbf{x}(0)$ has the mean $\bar{\mathbf{x}}_0$, covariance $\mathbf{P}_0$, and second moment $\boldsymbol{\Sigma}_0$.

Assumption 2. The process noise $\mathbf{w}(k)$ and measurement noise $\mathbf{v}(k)$ are zero-mean white processes with positive definite covariances $\boldsymbol{\Sigma}_{\mathbf{w}(k)}$ and $\boldsymbol{\Sigma}_{\mathbf{v}(k)}$.

Assumption 3. The parameter uncertainties $\mathbf{A}_\delta(k)$, $\mathbf{B}_\delta(k)$, $\mathbf{C}_\delta(k)$ are zero-mean white processes with

$$\begin{aligned} \mathbb{E}\left\{\mathrm{p}_{\text{row}}(\mathbf{A}_\delta(k))\mathrm{p}_{\text{row}}(\mathbf{A}_\delta(k))^T\right\} &= \boldsymbol{\Sigma}_{\mathbf{A}_\delta(k)}, \\ \mathbb{E}\left\{\mathrm{p}_{\text{row}}(\mathbf{B}_\delta(k))\mathrm{p}_{\text{row}}(\mathbf{B}_\delta(k))^T\right\} &= \boldsymbol{\Sigma}_{\mathbf{B}_\delta(k)}, \\ \mathbb{E}\left\{\mathrm{p}_{\text{row}}(\mathbf{C}_\delta(k))\mathrm{p}_{\text{row}}(\mathbf{C}_\delta(k))^T\right\} &= \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)}. \end{aligned} \tag{9}$$

Besides, the initial state, process noise, measurement noise, and parameter uncertainties are mutually independent of each other.

In this paper, our main purpose is to develop an effective method to detect both the occurrence and disappearance of intermittent additive and multiplicative sensor faults. Our method could be modified to extend to more general systems, such as even-triggered networked control systems [37,38], nonlinear systems, etc. Besides, it could also be extended to the situation of non zero-mean noise and parameter uncertainties, thus without any loss of generality.

3. Main results

The structure of our proposed robust filter is as follows:

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k)\mathbf{r}(k|k-1), \tag{10}$$

where

$$\hat{\mathbf{x}}(\mathbf{k}|\mathbf{k}-\mathbf{1}) = \mathbf{A_c}(\mathbf{k}-\mathbf{1})\hat{\mathbf{x}}(\mathbf{k}-\mathbf{1}) + \mathbf{B_c}(\mathbf{k}-\mathbf{1})\mathbf{u}(\mathbf{k}-\mathbf{1}), \tag{11}$$

$$\mathbf{r}(k|k-1) = \mathbf{y}(k) - \mathbf{C}_c(k)\hat{\mathbf{x}}(k|k-1), \tag{12}$$

and $\mathbf{K}(k)$ is the gain to be designed.

Next, we will show how to design the gain $\mathbf{K}(k)$ more specifically.

Theorem 1. *Consider the normal system (1)–(2), the gain of the filter (10)–(12) achieving minimum state estimation error covariance is given by*

$$\mathbf{K}(k) = \mathbf{H}(k)\mathbf{C}_c(k)^T\mathbf{Q}(k)^{-1}, \tag{13}$$

where

$$\begin{aligned}\mathbf{H}(k) = {} & \mathbf{A}_c(k-1)\mathbf{P_x}(k-1)\mathbf{A}_c(k-1)^T \\ & + \boldsymbol{\Sigma}_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{w}(k-1)},\end{aligned} \tag{14}$$

$$\mathbf{Q}(k) = \mathbf{C}_c(k)\mathbf{H}(k)\mathbf{C}_c(k)^T + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\boldsymbol{\Sigma}_{\mathbf{x}(k)}} + \boldsymbol{\Sigma}_{\mathbf{v}(k)}. \tag{15}$$

And the corresponding minimum state estimation error covariance is

$$\mathbf{P_x}(k) = (\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}(k)\mathbf{C}_c(k))\mathbf{H}(k). \tag{16}$$

Proof. According to (1)–(2),(10)–(12), it can be obtained that

$$\begin{aligned}\tilde{\mathbf{x}}(k) = {} & (\mathbf{A}_c(k-1) - \mathbf{K}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1))\tilde{\mathbf{x}}(k-1) \\ & + (\mathbf{A}_\delta(k-1) - \mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{A}_\delta(k-1) \\ & + \mathbf{C}_\delta(k)\mathbf{A}_c(k-1) + \mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)))\mathbf{x}(k-1) \\ & + (\mathbf{B}_\delta(k-1) - \mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{B}_\delta(k-1) \\ & + \mathbf{C}_\delta(k)\mathbf{B}_c(k-1) + \mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)))\mathbf{u}(k-1) \\ & + (\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}(k)(\mathbf{C}_c(k) + \mathbf{C}_\delta(k)))\mathbf{w}(k-1) - \mathbf{K}(k)\mathbf{v}(k).\end{aligned} \tag{17}$$

Then we can get the state estimation error covariance as follows:

$$\begin{aligned}\mathbf{P_x}(k) = {} & \mathbb{E}\{\tilde{\mathbf{x}}(k)\tilde{\mathbf{x}}(k)^T\} \\ = {} & \mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{A}_c(k-1)\mathbf{P_x}(k-1)\mathbf{A}_c(k-1)^T\mathbf{C}_c(k)^T \\ & + \mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)}\mathbf{C}_c(k)^T \\ & + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\mathbf{A}_c(k-1)\mathbf{x}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} \\ & + \boldsymbol{\mu}_{\mathbf{C}_\delta(k)(\mathbf{A}_c(k-1)\boldsymbol{\mu}_{\mathbf{x}(k-1)}\mathbf{u}(k-1)^T\mathbf{B}_c(k-1)^T)\mathbf{C}_\delta(k)^T} \\ & + \boldsymbol{\mu}_{\mathbf{C}_\delta(k)(\mathbf{B}_c(k-1)\mathbf{u}(k-1)\boldsymbol{\mu}_{\mathbf{x}(k-1)}{}^T\mathbf{A}_c(k-1)^T)\mathbf{C}_\delta(k)^T} \\ & + \mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{w}(k-1)}\mathbf{C}_c(k)^T + \mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)}\mathbf{C}_c(k)^T \\ & + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\mathbf{w}(k-1)} \\ & + \boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)\mathbf{B}_c(k-1)\mathbf{u}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{v}(k)})\mathbf{K}(k)^T \\ & + \mathbf{K}(k)(-\mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} \\ & - \mathbf{C}_c(k)\mathbf{A}_c(k-1)\mathbf{P_x}(k-1)\mathbf{A}_c(k-1)^T \\ & - \mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} - \mathbf{C}_c(k)\boldsymbol{\Sigma}_{\mathbf{w}(k-1)}) \\ & + (-\boldsymbol{\Sigma}_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)}\mathbf{C}_c(k)^T - \boldsymbol{\Sigma}_{\mathbf{w}(k-1)}\mathbf{C}_c(k)^T \\ & - \mathbf{A}_c(k-1)\mathbf{P_x}(k-1)\mathbf{A}_c(k-1)^T\mathbf{C}_c(k)^T \\ & - \boldsymbol{\Sigma}_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)}\mathbf{C}_c(k)^T)\mathbf{K}(k)^T \\ & + \mathbf{A}_c(k-1)\mathbf{P_x}(k-1)\mathbf{A}_c(k-1)^T \\ & + \boldsymbol{\Sigma}_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} + \boldsymbol{\Sigma}_{\mathbf{w}(k-1)} \\ = {} & \mathbf{K}(k)\mathbf{Q}(k)\mathbf{K}(k)^T - \mathbf{K}(k)\mathbf{C}_c(k)\mathbf{H}(k) + \mathbf{H}(k) \\ & - \mathbf{H}(k)\mathbf{C}_c(k)^T\mathbf{K}(k)^T \\ = {} & (\mathbf{K}(k)\mathbf{Q}(k) - \mathbf{H}(k)\mathbf{C}_c(k)^T) \\ & \times \mathbf{Q}(k)^{-1}(\mathbf{K}(k)\mathbf{Q}(k) - \mathbf{H}(k)\mathbf{C}_c(k)^T)^T \\ & - \mathbf{H}(k)\mathbf{C}_c(k)^T\mathbf{Q}(k)^{-1}\mathbf{C}_c(k)\mathbf{H}(k) + \mathbf{H}(k).\end{aligned} \tag{18}$$

It can be seen that $\mathbf{P_x}(k)$ is minimized when

$$\mathbf{K}(k) = \mathbf{H}(k)\mathbf{C}_c(k)^T\mathbf{Q}(k)^{-1}. \tag{19}$$

It is worth mentioning that $\mathbf{Q}(k)$ is positive definite and thus invertible. Furthermore, it can be derived that

$$\mathbf{P_x}(k) = (\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}(k)\mathbf{C}_c(k))\mathbf{H}(k). \tag{20}$$

The proof of this theorem is thus completed. □

The state estimation error covariance is bounded if the inequality $(1 + \|\mathbf{K}(k)\mathbf{C}_c(k)\|)\|\mathbf{A}_c(k-1)\| < 1$ holds [39,40].

Based on the above results, we can construct the residual generator as follows:

$$\mathbf{r}(k) = \mathbf{y}(k) - \mathbf{C}_c(k)\hat{\mathbf{x}}(k). \tag{21}$$

The basic property of our residual generator is given by the following theorem.

Theorem 2. *Consider the normal system (1)–(2) with initial state estimate $\hat{\mathbf{x}}(0) = \bar{\mathbf{x}}_0$, then the residual generator (21) has zero mean, i.e., $\mathbb{E}\{\mathbf{r}(k)\} = \mathbf{0}_{n_\mathbf{y}\times 1}$.*

Proof. It follows from $\hat{\mathbf{x}}(0) = \bar{\mathbf{x}}_0$ that $\mathbb{E}\{\mathbf{r}(0)\} = \mathbf{0}_{n_\mathbf{y}\times 1}$. Let $\tilde{\mathbf{x}}(k) = \mathbf{x}(k) - \hat{\mathbf{x}}(k)$ be the state estimation error, and assume inductively that the residual generator has zero mean for the integers from 0 to $k-1$, then it can be derived that

$$\begin{aligned}\mathbb{E}\{\mathbf{r}(k)\} = {} & \mathbb{E}\{\mathbf{C}_c(k)\tilde{\mathbf{x}}(k) + \mathbf{C}_\delta(k)\mathbf{x}(k) + \mathbf{v}(k)\} \\ = {} & \mathbb{E}\{(\mathbf{A}_c(k-1) - \mathbf{K}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1))\mathbf{r}(k-1) \\ & + (\mathbf{A}_\delta(k-1) - \mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{A}_\delta(k-1) \\ & + \mathbf{C}_\delta(k)\mathbf{A}_c(k-1) + \mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)))\mathbf{x}(k-1) \\ & + (\mathbf{B}_\delta(k-1) - \mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{B}_\delta(k-1) \\ & + \mathbf{C}_\delta(k)\mathbf{B}_c(k-1) + \mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)))\mathbf{u}(k-1) \\ & + (\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}(k)(\mathbf{C}_c(k) + \mathbf{C}_\delta(k)))\mathbf{w}(k-1) - \mathbf{K}(k)\mathbf{v}(k)\},\end{aligned} \tag{22}$$

which implies that $\mathbb{E}\{\mathbf{r}(k)\} = \mathbf{0}_{n_\mathbf{y}\times 1}$ always holds. The theorem is thus proved. □

As the residual is critical for IFD, we will make a detailed analysis of the relationship between the residual and the faults in the following theorem.

Theorem 3. *The residual $\mathbf{r}(k)$ as defined in (21) of the faulty system (1)–(2) is related to the fault by*

$$\begin{aligned}\mathbf{r}(\mathbf{k}) = {} & \mathbf{r}_o(k) + (\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}} + \mathbf{C}_c(k)\mathbf{S}(k))\mathbf{f}_a(k) \\ & + (\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}} + \mathbf{C}_c(k)\mathbf{Z}(k))\mathbf{E_f}(k)\mathbf{f}_m(k) + \mathbf{C}_c(k)(\mathbf{s}(k) + \mathbf{z}(k)),\end{aligned} \tag{23}$$

where $\mathbf{r}_o(k)$ denotes the residual of the normal system, and $\mathbf{S}(k)$, $\mathbf{Z}(k)$, $\mathbf{s}(k)$, $\mathbf{z}(k)$, $\mathbf{L}(k)$ have the following forms:

$$\mathbf{S}(k) = \mathbf{L}(k)\mathbf{S}(k-1) - \mathbf{K}(k), \tag{24}$$

$$\mathbf{Z}(k)\mathbf{E_F}(k) = \mathbf{L}(k)\mathbf{Z}(k-1)\mathbf{E_F}(k-1) - \mathbf{K}(k)\mathbf{E_F}(k), \tag{25}$$

$$\mathbf{s}(k) = \begin{cases} -(\mathbf{K}(k) + \mathbf{S}(k))\mathbf{f}_a(k) + \mathbf{L}(k)\mathbf{s}(k-1), k = k_{a,o,i}, \\ \mathbf{L}(k)(\mathbf{S}(k-1)\mathbf{f}_a(k-1) + \mathbf{s}(k-1)), k = k_{a,d,i}, \\ \mathbf{L}(k)\mathbf{s}(k-1), k \in \mathcal{S}(k_{a,d,i}+1, k_{a,o,i+1}-1), \\ \mathbf{0}_{n_\mathbf{x}\times 1}, \text{otherwise}, \end{cases} \tag{26}$$

$$\mathbf{z}(k) = \begin{cases} -(\mathbf{K}(k)+\mathbf{Z}(k))\mathbf{E_f}(k)\mathbf{f}_m(k)+\mathbf{L}(k)\mathbf{z}(k-1), & k=k_{m,o,i}, \\ \mathbf{L}(k)(\mathbf{Z}(k-1)\mathbf{E_f}(k-1)\mathbf{f}_m(k-1)+\mathbf{z}(k-1)), & k=k_{m,d,i}, \\ \mathbf{L}(k)\mathbf{z}(k-1), \quad k\in\mathcal{S}(k_{m,d,i}+1, k_{m,o,i+1}-1), & \\ \mathbf{0}_{n_\mathbf{x}\times 1}, & \text{otherwise}, \end{cases} \tag{27}$$

$$\mathbf{L}(k) = (\mathbf{A}_c(k-1) - \mathbf{K}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)). \tag{28}$$

Proof. The state estimation error and residual of the faulty system are

$$\begin{aligned}\tilde{\mathbf{x}}(k) &= \mathbf{L}(k)\tilde{\mathbf{x}}(k-1)+\mathbf{N}(k)\mathbf{x}(k-1)+\mathbf{M}(k)\mathbf{u}(k-1)\\ &\quad+\mathbf{U}(k)\mathbf{w}(k-1)-\mathbf{K}(k)\mathbf{v}(k)-\mathbf{K}(k)\mathbf{f}_a(k)\\ &\quad-\mathbf{K}(k)\mathbf{F}_m(k)(\mathbf{C}_c(k)+\mathbf{C}_\delta(k))\mathbf{x}(k),\end{aligned} \tag{29}$$

$$\begin{aligned}\mathbf{r}(k) &= \mathbf{C}_c(k)\tilde{\mathbf{x}}(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)+\mathbf{f}_a(k)\\ &\quad+\mathbf{F}_m(k)(\mathbf{C}_c(k)+\mathbf{C}_\delta(k))\mathbf{x}(k),\end{aligned} \tag{30}$$

where

$$\mathbf{L}(k) = (\mathbf{A}_c(k-1) - \mathbf{K}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)), \tag{31}$$

$$\begin{aligned}\mathbf{N}(\mathbf{k}) &= (\mathbf{A}_\delta(k-1)-\mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{A}_\delta(k-1)\\ &\quad+\mathbf{C}_\delta(k)\mathbf{A}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1))),\end{aligned} \tag{32}$$

$$\begin{aligned}\mathbf{M}(\mathbf{k}) &= (\mathbf{B}_\delta(k-1)-\mathbf{K}(k)(\mathbf{C}_c(k)\mathbf{B}_\delta(k-1)\\ &\quad+\mathbf{C}_\delta(k)\mathbf{B}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1))),\end{aligned} \tag{33}$$

$$\mathbf{U}(k) = (\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}(k)(\mathbf{C}_c(k)+\mathbf{C}_\delta(k))). \tag{34}$$

Now let us define the variables $\boldsymbol{\alpha}(k)$ and $\boldsymbol{\beta}(k)$ as follows:

$$\boldsymbol{\alpha}(k) = \tilde{\mathbf{x}}(k) - 2\mathbf{S}(k)\mathbf{f}_a(k) - 2\mathbf{s}(k), \tag{35}$$

$$\boldsymbol{\beta}(k) = \tilde{\mathbf{x}}(k) - 2\mathbf{Z}(k)\mathbf{E_f}(k)\mathbf{f}_m(k) - 2\mathbf{z}(k), \tag{36}$$

where $\mathbf{S}(k)$, $\mathbf{Z}(k)$, $\mathbf{s}(k)$, and $\mathbf{z}(k)$ are defined in (24)–(27). It then follows immediately from (29)–(30), and (35)–(36) that

$$\begin{aligned}\mathbf{r}(k) &= \mathbf{C}_c(k)\tilde{\mathbf{x}}_o(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)\\ &\quad+\mathbf{f}_a(k)+\mathbf{C}_c(k)\mathbf{S}(k)\mathbf{f}_a(k)+\mathbf{C}_c(k)\mathbf{s}(k)\\ &\quad+\mathbf{F}_m(k)(\mathbf{C}_c(k)+\mathbf{C}_\delta(k))\mathbf{x}(k)+\mathbf{C}_c(k)\mathbf{z}(k)\\ &\quad+\mathbf{C}_c(k)\mathbf{Z}(k)\mathbf{F}_m(k)(\mathbf{C}_c(k)+\mathbf{C}_\delta(k))\mathbf{x}(k)\\ &= \mathbf{r}_o(k)+(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}+\mathbf{C}_c(k)\mathbf{S}(k))\mathbf{f}_a(k)\\ &\quad+(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}+\mathbf{C}_c(k)\mathbf{Z}(k))\mathbf{E_f}(k)\mathbf{f}_m(k)+\mathbf{C}_c(k)(\mathbf{s}(k)+\mathbf{z}(k)).\end{aligned} \tag{37}$$

The proof of this theorem is thus completed. □

Below is a direct corollary of the above theorem.

Corollary 1. *Consider the faulty system (1)–(2) with residual generator (21), then the faults are detectable if the following condition holds:*

$$\begin{aligned}&(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}+\mathbf{C}_c(k)\mathbf{S}(k))\mathbf{f}_a(k)+(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}+\mathbf{C}_c(k)\mathbf{Z}(k))\mathbf{E_f}(k)\mathbf{f}_m(k)\\ &\quad+\mathbf{C}_c(k)(\mathbf{s}(k)+\mathbf{z}(k))\neq\mathbf{0}_{n_\mathbf{y}\times 1},\\ &\forall k\in[k_{a,o,i}, k_{a,d,i}-1]\cup[k_{m,o,i}, k_{m,d,i}-1], \quad i\in\mathbb{N}^+,\end{aligned} \tag{38}$$

where $\mathbf{r}_o(k)$ denotes the residual of the normal system, and $\mathbf{S}(k)$, $\mathbf{Z}(k)$, $\mathbf{s}(k)$, $\mathbf{z}(k)$, $\mathbf{L}(k)$ are defined in (24)–(28).

The detection statistic has the following square form:

$$T_D(k) = \mathbf{r}(k)^T\mathbf{r}(k). \tag{39}$$

And the corresponding detection threshold is set as

$$J_D(k) = \sup_{\mathbf{f}_a(k)\equiv\mathbf{0}_{n_\mathbf{y}\times 1}, \mathbf{F}_m(k)\equiv\mathbf{0}_{n_\mathbf{y}\times n_\mathbf{y}}} \mathbb{E}\{T_D(k)\}. \tag{40}$$

Then the occurrence and disappearance of sensor faults can be determined by the following logic:

$$\begin{cases} T_D(k) > J_D(k) \Rightarrow \text{with fault} \Rightarrow \text{fault alarm}, \\ T_D(k) \le J_D(k) \Rightarrow \text{no fault} \Rightarrow \text{fault release}. \end{cases} \tag{41}$$

The detection statistic is time-varying, so it is suitable to set the threshold at each time step.

4. Simulation example

In this section, a numerical example is given to show the effectiveness of our obtained results. Consider the stochastic LTV system with the following parameters:

$$\mathbf{A}_c(k) = \begin{bmatrix} 0.96+0.01\sin(0.15k) & 0.16 \\ 0.18 & -0.74+0.02\cos(0.12k) \end{bmatrix},$$

$$\mathbf{B}_c(k) = \begin{bmatrix} 0.3+0.01\cos(0.12k) \\ 0.5+0.01\sin(0.16k) \end{bmatrix},$$

$$\mathbf{C}_c(k) = \begin{bmatrix} 0.97 & 0.43+0.02\cos(0.15k) \\ -0.65+0.01\sin(0.12k) & 0.86 \end{bmatrix}.$$

In our simulation, the stochastic additive variables are the initial state, process noise, and measurement noise which are mutually independent zero-mean white noise processes with covariances $\boldsymbol{\Sigma}_{\mathbf{x}(0)} = \mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}}\times 10^{-6}$, $\boldsymbol{\Sigma}_{\mathbf{w}(k)} = 1.2\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}}\times 10^{-6}$, and $\boldsymbol{\Sigma}_{\mathbf{v}(k)} = 1.4\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}\times 10^{-6}$, respectively. The stochastic multiplicative variables are the parameter uncertainties which are mutually independent zero-mean white noise processes with covariances

$$\boldsymbol{\Sigma}_{\mathbf{A}_\delta(k)} = \begin{bmatrix} 1+0.1\cos(0.12k) & & & \\ & 1.3 & & \\ & & 1+0.2\sin(0.1k) & \\ & & & 1.1 \end{bmatrix}\times 10^{-6},$$

$$\boldsymbol{\Sigma}_{\mathbf{B}_\delta(k)} = \begin{bmatrix} 1.2+0.1\sin(0.12k) & \\ & 1.4+0.1\cos(0.15k) \end{bmatrix}\times 10^{-6},$$

$$\boldsymbol{\Sigma}_{\mathbf{C}_\delta(k)} = \begin{bmatrix} 1.3 & & & \\ & 1+0.5\sin(0.16k) & & \\ & & 1.2 & \\ & & & 1+0.1\cos(0.15k) \end{bmatrix}\times 10^{-6}.$$

In order to fully illustrate the validity of our proposed method, various fault cases are all considered.

Case 1. Only additive fault occurs:

$$\mathbf{f}_a(k) = \begin{cases} \begin{bmatrix} 0.7 & 0 \end{bmatrix}^T, & k\in[201, 400], \\ \begin{bmatrix} 0 & 0.8 \end{bmatrix}^T, & k\in[601, 800], \\ \begin{bmatrix} 0.8 & 0.6 \end{bmatrix}^T, & k\in[1001, 1300], \\ \begin{bmatrix} 0 & 0 \end{bmatrix}^T, & \text{otherwise}. \end{cases}$$

$\mathbf{F}_m(k) = \mathbf{0}_{2\times 2}, k\in[0, 1500].$

Case 2. Only multiplicative fault occurs:

$$\mathbf{F}_m(k) = \begin{cases} \begin{bmatrix} 0.3 & \\ & 0 \end{bmatrix}, & k\in[201, 400], \\ \begin{bmatrix} 0 & \\ & 0.5 \end{bmatrix}, & k\in[601, 800], \\ \begin{bmatrix} 0.4 & \\ & 0.6 \end{bmatrix}, & k\in[1001, 1300], \\ \mathbf{0}_{2\times 2}, & \text{otherwise}. \end{cases}$$

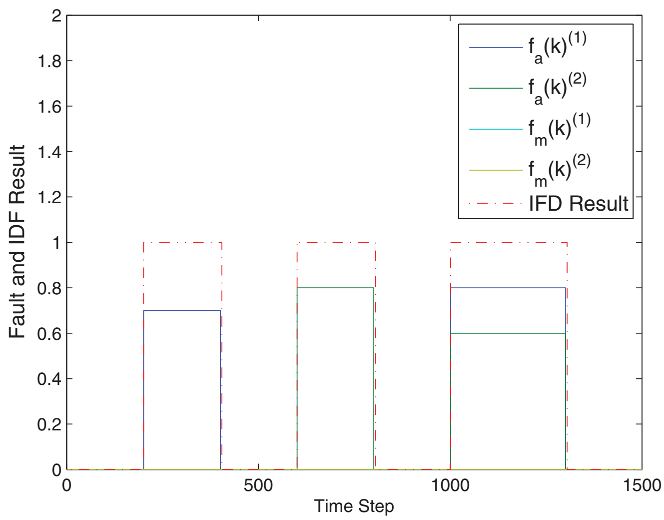

Fig. 1. Detection result of faults in Case 1.

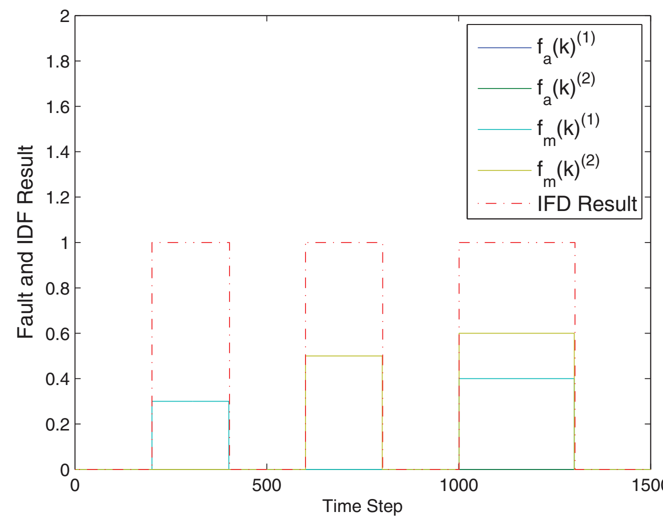

Fig. 2. Detection result of faults in Case 2.

$\mathbf{f}_a(k) = \mathbf{0}_{2\times 1}, k \in [0, 1500]$.

Case 3. Both additive and multiplicative faults occur:

$$\mathbf{f}_a(k) = \begin{cases} \begin{bmatrix} 0.8 & 0 \end{bmatrix}^T, & k \in [201, 400], \\ \begin{bmatrix} 0 & 0.7 \end{bmatrix}^T, & k \in [701, 900], \\ \begin{bmatrix} 0.6 & 0.8 \end{bmatrix}^T, & k \in [1001, 1300], \\ \begin{bmatrix} 0 & 0 \end{bmatrix}^T, & \text{otherwise.} \end{cases}$$

$$\mathbf{F}_m(k) = \begin{cases} \begin{bmatrix} 0 & \\ & 0.6 \end{bmatrix}, & k \in [301, 500], \\ \begin{bmatrix} 0.4 & \\ & 0 \end{bmatrix}, & k \in [601, 800], \\ \begin{bmatrix} 0.5 & \\ & 0.3 \end{bmatrix}, & k \in [1001, 1300], \\ \mathbf{0}_{2\times 2}, & \text{otherwise.} \end{cases}$$

Case 4. Both positive and negative faults occur:

$$\mathbf{f}_a(k) = \begin{cases} \begin{bmatrix} 0 & 0.6 \end{bmatrix}^T, & k \in [301, 500], \\ \begin{bmatrix} -0.7 & 0 \end{bmatrix}^T, & k \in [601, 800], \\ \begin{bmatrix} 0.8 & -0.7 \end{bmatrix}^T, & k \in [1001, 1300], \\ \begin{bmatrix} 0 & 0 \end{bmatrix}^T, & \text{otherwise.} \end{cases}$$

$$\mathbf{F}_m(k) = \begin{cases} \begin{bmatrix} -0.5 & \\ & 0 \end{bmatrix}, & k \in [201, 400], \\ \begin{bmatrix} 0 & \\ & 0.3 \end{bmatrix}, & k \in [701, 900], \\ \begin{bmatrix} & -0.4 \\ -0.5 & \end{bmatrix}, & k \in [1001, 1300], \\ \mathbf{0}_{2\times 2}, & \text{otherwise.} \end{cases}$$

Simulation results are shown in Figs. 1–4. It can be seen that our method could detect both the occurrence and disappearance of sensor faults very well regardless of faulty sensors (sensor 1/sensor 2) or fault profile (positive/negative). Besides, regardless of how the additive and multiplicative faults occur, alone or simultaneously,

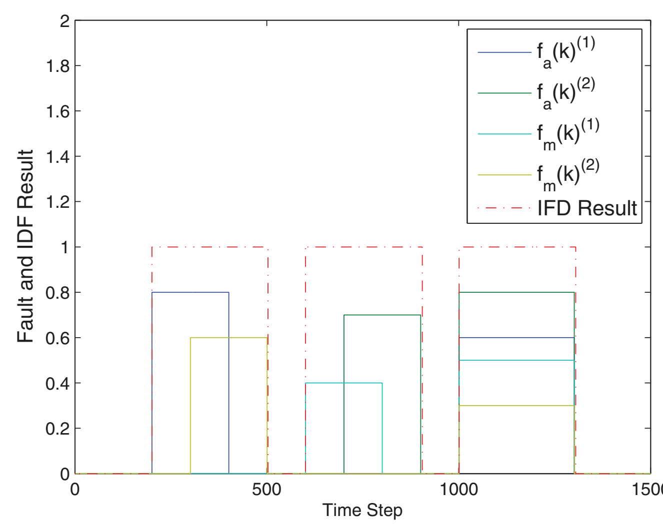

Fig. 3. Detection result of faults in Case 3.

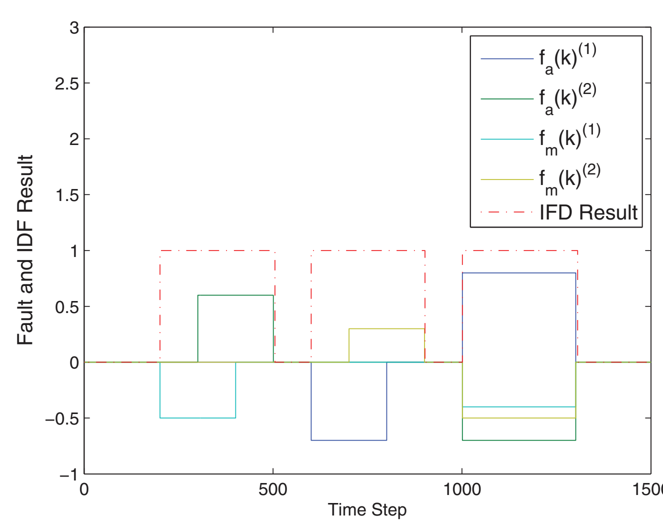

Fig. 4. Detection result of faults in Case 4.

our method always has favorable performance. This successfully demonstrates the effectiveness of our proposed method.

5. Conclusion

In this paper, we have investigated the IFD problem for stochastic uncertain LTV systems with both additive and multiplicative sensor faults. By resorting to linear system theory and stochastic analysis methods, we have proposed a real-time online IFD method to detect both the occurrence and disappearance of sensor faults. Furthermore, we have also given the detectability conditions of both additive and multiplicative sensor faults. Finally, we have demonstrated the effectiveness of our method through an illustrative example.

Declaration of Competing Interest

We would like to submit the enclosed manuscript entitled “Robust Detection of Intermittent Sensor Faults in Stochastic LTV Systems”, which we wish to be considered for publication in “Neurocomputing”. No conflict of interest exits in the submission of this manuscript, and the manuscript is approved by all authors for publication. Our work is original which has not been published previously nor considered for publication elsewhere, in whole or in part. We deeply appreciate your consideration of our manuscript, and look forward to receiving comments from the reviewers.

CRediT authorship contribution statement

Junfeng Zhang: Conceptualization, Data curation, Writing - original draft. **Panagiotis D. Christofides:** Conceptualization, Data curation, Writing - original draft. **Xiao He:** Conceptualization, Data curation, Writing - original draft. **Zhe Wu:** Conceptualization, Data curation, Writing - original draft. **Yinghong Zhao:** Conceptualization, Data curation, Writing - original draft. **Donghua Zhou:** Conceptualization, Data curation, Writing - original draft.

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