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Research article

Multiple incipient sensor faults diagnosis with application to high-speed railway traction devices ☆

Yunkai Wu [a], Bin Jiang [a,*], Ningyun Lu [a], Hao Yang [b], Yang Zhou [a]

[a] College of Automation Engineering and Jiangsu Key Laboratory of Internet of Things and Control Technologies, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, PR China
[b] School of Computer Science and Engineering, Jiangsu University of Science and Technology, Zhenjiang 212003, PR China

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ABSTRACT

This paper deals with the problem of incipient fault diagnosis for a class of Lipschitz nonlinear systems with sensor biases and explores further results of total measurable fault information residual (ToMFIR). Firstly, state and output transformations are introduced to transform the original system into two subsystems. The first subsystem is subject to system disturbances and free from sensor faults, while the second subsystem contains sensor faults but without any system disturbances. Sensor faults in the second subsystem are then formed as actuator faults by using a pseudo-actuator based approach. Since the effects of system disturbances on the residual are completely decoupled, multiple incipient sensor faults can be detected by constructing ToMFIR, and the fault detectability condition is then derived for discriminating the detectable incipient sensor faults. Further, a sliding-mode observers (SMOs) based fault isolation scheme is designed to guarantee accurate isolation of multiple sensor faults. Finally, simulation results conducted on a CRH2 high-speed railway traction device are given to demonstrate the effectiveness of the proposed approach.

1. Introduction

Modern control systems have been becoming extensively integrated and complex. Along with growth of the running time, actuators and sensors in the control systems are degrading with age, therefore, FDD (Fault Detection and Diagnosis) and fault tolerant techniques have been extensively studied and widely employed in practical applications [1–11]. Meanwhile, these fatigued components are likely to have various slowly developing faults (i.e., incipient faults), which will increase the risk of serious accidents in the entire systems. However, researches on incipient fault diagnosis [12–16] are quite few due to the challenges that incipient faults are almost unnoticeable during their initial stage and their effects to residuals are often concealed by system disturbances.

Sensors in control systems are used to collect system information, which do not affect system performance directly, thus FDD of sensor faults are much more difficult compared with that of actuator faults (e.g. [17] and [18]). As regards the common sensor faults, a few research results have been reported. For example, an adaptive estimation based sensor fault detection and isolation scheme has been developed in [19] for a class of Lipschitz nonlinear systems with unstructured modeling uncertainty. To assure robustness of the sensor fault diagnosis method for the system with unstructured modeling uncertainty, adaptive decision thresholds were proposed in [20]. The Effects of time delay between the sensor fault occurrence and the fault accommodation on the system performance were investigated in [21], where an adaptive fault diagnosis scheme was proposed to minimize the adverse effect. In [22], sensor fault estimation and compensation for time-delay switched systems were investigated based on a switched descriptor observer approach. What's more, sensor fault estimation and compensation technique proposed in [23] has been applied on micro-satellite attitude control systems successfully.

Beside the existing difficulties for sensor fault diagnosis, industrial applications impose even more challenges, for example, the frequently encountered multiple faults. There are a few research results on FDD of common multiple faults [24–26] and some achievements have been applied in practical applications (e.g. [27] and [28]). Focusing on FDD of multiple sensor faults, a data-driven method has been proposed in [29], which was applied to continuous-flow stirred-tank reactor. In addition, an ant-search strategy based multiple fault diagnosis approach was proposed for industrial sensor networks in [30]. However, the studies of

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* Corresponding author.
E-mail address: binjiang@nuaa.edu.cn (B. Jiang).

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analytical model-based multiple fault diagnosis are quite few.

The aforementioned FDD methods can be considered as the successful pioneer work for sensor faults or even multiple sensor faults. However, these methods haven't considered the influence of closed-loop control configuration. According to [31], FDD in closed-loop systems is quite different from that in open-loop cases. The main reason is that closed-loop systems usually have robustness against external disturbances or even faults. Some efforts have been made to solve this problem. For example, the best location to collect fault residuals was studied in [32]. An adaptive threshold based FDD approach was presented to eliminate the effect of closed-loop controller in [33]. But in general, FDD in closed-loop systems is still a challenging problem. Aiming at incipient fault detection in closed-loop systems, total measurable fault information residual (ToMFIR), was developed in [34] and [35]. However, the original approaches and our preliminary work based on ToMFIR in [36] are merely suitable for linear and time-invariant systems. In this paper, an improved ToMFIR-based FDD approach for multiple incipient sensor faults is proposed for nonlinear Lipschitz systems. The original system is transformed into two subsystems where the first subsystem contains system disturbances but is free from sensor faults and the second subsystem is only subject to sensor faults without any disturbances. Constructing ToMFIR based on the transformed system structure, one can achieve a better sensor fault detection method compared with the observer residual based approaches. What's more, the proposed method takes system disturbances into consideration and becomes a more general FDD framework. The incipient fault isolation scheme proposed in this paper is capable of isolating multiple sensor faults even if they occur at the same time.

The organization of the remaining parts are as follows. In Section 2, the mathematical preliminaries required for designing a diagnosis scheme and a system decomposition are briefly described. An improved incipient FDD scheme is presented in Section 3, including multiple incipient sensor fault detection and isolation. Extensive simulations on an induction motor system equipped in CRH2 high-speed trains are performed to illustrate the effectiveness of the proposed method. Conclusions are drawn in Section 5.

2. Problem formulation

This paper considers a class of nonlinear dynamic systems, denoted by G, and its nominal form, denoted by G_N,

$$G:\begin{cases}\dot{x}(t)=Ax(t)+f(x,t)+Bu(t)+E\Delta\varphi(t)\\ y(t)=Cx(t)+F\beta(t-T_0)\theta_s(t)\end{cases}\tag{1}$$

$$G_N:\begin{cases}\dot{x}_N(t)=Ax_N(t)+f(x_N,t)+Bu_N(t)\\ y_N(t)=Cx_N(t)\end{cases}\tag{2}$$

where $x\in R^n$, $u\in R^m$ and $y\in R^p$ represent the real state variable, inputs and outputs; similarly, $x_N\in R^n$, $u_N\in R^m$ and $y_N\in R^p$ denote the nominal state variable, inputs and outputs, respectively; $A\in R^{n\times n}$, $B\in R^{n\times m}$, $C\in R^{p\times n}$, $E\in R^{n\times r}$ and $F\in R^{p\times q}$ are constant matrices; C and F are of full rank. $f(x,t)\in R^n$ and $f(x_N,t)\in R^n$ are the nonlinear terms of real nonlinear model and nominal nonlinear model respectively, which satisfy the Lipschitz constraints in Assumption 2. The unknown nonlinear term $\Delta\varphi(t)\in R^r$ denotes modeling uncertainties or external disturbance signals.

From a qualitative viewpoint, the term $F\beta(t-T_0)\theta_s(t)$ denotes the change in the system dynamic as a result of the occurrence of an incipient sensor fault, where the vector $F\in R^{p\times q}$ can indicate the location of the senor fault, and the vector $\theta_s(t)\in R^q$ represents unknown time-varying sensor biases. The matrix $\beta(t-T_0)\in R^{q\times q}$ that characterizes the time profile of a fault occurred at T_0 (unknown in advance), is a diagonal matrix,

$$\beta(t-T_0)=diag\left[\beta_1(t-T_0),\beta_2(t-T_0),\dots,\beta_q(t-T_0)\right]\tag{3}$$

where $\beta_i(t-T_0)$: $R\to R$ is a function representing the time profile of a fault affecting the i–th state equation, for $i=1,2,\dots,q$, where q is the number of the sensors. According to [20], the time profiles can be modeled as

$$\beta_i(t-T_0)=\begin{cases}0 & \text{if } t<T_0\\ 1-e^{-a_i(t-T_0)} & \text{if } t\ge T_0\end{cases}\tag{4}$$

where the scalar $a_i>0$ denotes the unknown fault evolution rate. Small a_i can characterize incipient (slowly developing) faults. For an increasing a_i, the time profile $\beta_i(t-T_0)$ approaches to a step function, which can describe an abrupt fault. Note that the time profile only reflects the evolving speed of the fault, while the other features, like frequency and amplitude, can be described by $\theta_s(t)$. For fault isolation purpose, one can assume that there are q types of possible sensor faults. $\theta_s(t)$ belongs to a finite set of functions given by $\theta_s(t)=\left[\theta_s^{1^T},\theta_s^{2^T},\dots,\theta_s^{q^T}\right]^T$.

Assumption 1. $rank(B)=m$, $rank(E)=r$, $rank\left(C\left[BE\right]\right)=m+r$.

Assumption 2. The nonlinear term $f(x,t)$ and $f(x_N,t)$ are assumed to be Lipschitz about x and x_N locally, i.e., $\forall\ \|x\|\le X$, $\|x'\|\le X$, $\forall\ \|x_N\|\le X_N$, $\|x'_N\|\le X_N$, s.t.

$$\|f(x,t)-f(x',t)\|\le L_f\|x-x'\|,\ \|f(x_N,t)-f(x'_N,t)\|\le L'_f\|x_N-x'_N\|\tag{5}$$

where X and X_N are positive constants, L_f and L'_f are the known Lipschitz constants.

Assumption 3. $\Delta\varphi(t)$ is unknown but bounded, and it satisfies $\|\Delta\varphi(t)\|\le\bar{\varphi}$, $\forall\ t\ge0$. Also, the unknown sensor fault is norm bounded, and the change rate of a time-varying sensor bias is uniformly bounded, i.e., $\|\theta_s(t)\|\le\bar{\theta}$, $\|\dot{\theta}_s(t)\|\le\bar{\bar{\theta}}$. $\bar{\varphi}$, $\bar{\theta}$, and $\bar{\bar{\theta}}$ are positive scalars known in advance.

Assumption 4. For every complex number s with non-negative real part

$$rank\begin{bmatrix}sI_n-A & B\\ C & 0\end{bmatrix}=n+rank(B)\tag{6}$$

This assumption is known as the minimum phase condition.

Assumption 1 can ensure the existence of two coordinate transformations $z=Tx=\left[z_1^Tz_2^T\right]^T$, $\eta=Sy=\left[\eta_1^T\eta_2^T\right]^T$ with $z_1\in R^r$, $z_2\in R^{n-r}$, $\eta_1\in R^r$ and $\eta_2\in R^{n-r}$, such that

- $TAT^{-1}=\begin{bmatrix}A_{11} & A_{12}\\ A_{21} & A_{22}\end{bmatrix}$, where $A_{11}\in R^{r\times r}$, $A_{12}\in R^{r\times(n-r)}$, $A_{21}\in R^{(n-r)\times r}$, $A_{22}\in R^{(n-r)\times(n-r)}$.
- $TB=\begin{bmatrix}B_1\\ B_2\end{bmatrix}$, where $B_1\in R^{r\times m}$, $B_2\in R^{(n-r)\times m}$.
- $TE=\begin{bmatrix}E_1\\ 0\end{bmatrix}$, where $E_1\in R^{r\times r}$.
- $SCT^{-1}=\begin{bmatrix}C_{11} & 0\\ 0 & C_{22}\end{bmatrix}$, where $C_{11}\in R^{r\times r}$, $C_{22}\in R^{(p-r)\times(n-r)}$.
- $SF=\begin{bmatrix}0\\ F_2\end{bmatrix}$, where $F_2\in R^{(p-r)\times q}$.

Thus, the original nonlinear system G can be transformed into two subsystems

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