Active Fault-Tolerant Control for a Class of Nonlinear Systems with Sensor Faults

Youqing Wang, Donghua Zhou, S. Joe Qin, and Hong Wang

Abstract: A general active fault-tolerant control framework is proposed for nonlinear systems with sensor faults. According to their identifiability, all sensor faults are divided into two classes: identifiable faults and non-identifiable faults. In the healthy case, the control objective is such that all outputs converge to their given set-points. A fault detection and isolation module is firstly built, which can produce an alarm when there is a fault in the system and also tell us which sensor has a fault. If the fault is identifiable, the control objective remains the same as in the healthy case; while if the fault is non-identifiable, the control objective degenerates to be such that only the healthy outputs converge to the set-points. A numerical example is given to illustrate the effectiveness and feasibility of the proposed method and encouraging results have been obtained.

Keywords: Active fault-tolerant control, identifiable fault, non-identifiable fault, nonlinear system, sensor fault.

1. INTRODUCTION

The demand for productivity leads increasingly for industrial plants to operate under challenging conditions, which consequently exposes the possibility of systems fault. This is because industrial processes typically have a large number of sensors and actuators. If a fault is not detected promptly with a proper corrective action, it will degrade the process performance and in a more serious case, even results in safety problems for the plant and personnel. In this context, a fault-tolerant controller, which is capable of maintaining the performance of the closed-loop system at an acceptable level in the presence of faults, is desirable. Because of this, fault-tolerant control using model-based analysis redundancy has received significant attention recently (e.g., [1-5]).

Since sensor faults are very common in industrial systems, fault-tolerant control for sensor faults has to be considered. Depending on whether a fault diagnosis module is used, fault-tolerant control can be divided into two kinds: passive method and active method. For the passive method, the main task is to design a fixed controller such that the closed-loop system can maintain closed loop system stability and performance, not only when all components are operational, but also in the case of faults. In [6], Yang *et al.* proposed a reliable LQG controller for linear systems with sensor faults by solving Riccati equations. In [7], a more practical model of sensor faults was introduced and H_∞ performance of the closed-loop system was considered. In [8], Yee *et al.* designed a reliable controller for discrete-time linear systems based on the iterative LMI approach.

In an active fault-tolerant system, a new control law is redesigned using desirable properties of performance and robustness that were important in the original system, but with the reduced capability of the impaired system in mind. In order to achieve effective feedback control reconfiguration, a fault diagnosis module is generally required in an active fault-tolerant system. In [9], Trunov and Polycarpou presented a learning scheme to detect and approximate sensor faults occurring in a class of nonlinear multi-input multi-output dynamical systems. The method was robust with respect to bounded modeling uncertainties. In [10], a wavelet-based approach to the abrupt fault detection and diagnosis of sensors was described. Two methods for detecting and reconstructing sensor faults using sliding mode observers were proposed in [11]. In [12], Wang *et al.* used adaptive updating rules for

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the fault detection and diagnosis of sensor gain faults in a linear time-invariant system. Based on a bilinear model and a fault-tolerant observer, an active fault-tolerant control law was proposed for a rail traction drive with sensor intermittent disconnection faults in [13]. [14] presented a fault-tolerant control for a ship propulsion benchmark, where estimated or virtual measurements were used as feedback variables. The estimator operates on a self-adjustable design model so that its outputs can be made immune to the effects of a specific set of sensor faults. In [15], Jeong *et al.* proposed a control strategy that provides fault tolerance to the major sensor faults which may occur in an interior-permanent-magnet-motor (IPMM)-based electric vehicle propulsion drive system.

In [16], identifiability of sensor faults was studied and a novel approach to fault detection and diagnosis of a class of nonlinear systems is presented. All sensor faults are divided into two classes: the conditionally identifiable faults and the conditionally detectable faults. The above results will be extended to fault-tolerant control in this paper. The formulation of considered system is the same as that considered in [16]. Similarly, all sensor faults are divided into two classes: identifiable faults and non-identifiable faults. Firstly, a fault detection observer is proposed to detect the fault. If a fault alarm is produced, then some fault isolation observers are activated to determine which sensor has a fault. If the fault is identifiable, the control objective remains the same as that in healthy case: that is to regulate all outputs to their set-points. If the fault is non-identifiable, the control objective degenerates to regulate only the healthy outputs to their set-points. All proposed observers are designed based on LMIs, which can be solved efficiently by using toolbox in MATLAB. The feasibility and effectiveness of the proposed schemes are illustrated in a numerical example.

The remainder of the paper is organized as follows. In Section 2, the problem formulation is presented. The fault detection and isolation modules are developed in Section 3. The fault diagnosis observer is presented in Section 4. The normal controller and fault-tolerant controller are designed and analyzed in Section 5. To demonstrate the effectiveness of the proposed scheme, Section 6 gives some simulation results. Finally, conclusions are drawn in Section 7.

2. PROBLEM FROMULATION

In this paper, the nonlinear dynamical systems under study are described as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + g(x,u,t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{1}$$

where $x \in \mathbb{R}^n$ is the state vector; $u \in \mathbb{R}^p$ is the input vector; $y \in \mathbb{R}^m$ is the output vector; $g(x,u,t)$ is a smooth vector field on $\mathbb{R}^n$; A, B, C are known parameter matrices of appropriate dimensions. For convenience, the controlled output is chosen as

$$z(t) = Cx(t), \tag{2}$$

which is a fictitious variable of the state vector.

Bias faults and gain faults are two kinds of sensor faults commonly existing in practice. A sensor bias fault can be described as:

$$y(t) = z(t) + f(t) \tag{3}$$

and a sensor gain fault can be described as:

$$y(t) = \left(1 - \Gamma(t)\right) z(t), \tag{4}$$

where $0 \le \Gamma(t) \le I$ is called attenuation matrix. Obviously, equation (4) can be rewritten as

$$y(t) = z(t) - \Gamma(t)z(t) = z(t) + f(x,t). \tag{5}$$

Therefore, the above two kinds of sensor faults can be uniformly described as

$$y(t) = z(t) + f(x,t). \tag{6}$$

In this paper, both bias and gain faults are studied.

Since $y \in \mathbb{R}^m$, there are m sensor faults to be considered. In practice, it is infrequent that two or more than two sensor faults occur simultaneously. Therefore, the following assumptions are made.

Assumption 1: Only one single fault might occur at one time.

If there is a fault in sensor i, then

$$y_i(t) = z_i(t) + f_i(x,t) = C_i x(t) + f_i(x,t), \tag{7}$$

where $C_i \in \mathbb{R}^{1\times n}$ denotes the i th row vector of matrix C.

Assumption 2: (A, C) is detectable.

Assumption 3: $g(x,u,t)$ is *globally Lipschitz* with respect to x, i.e.,

$$\|g(x_1,u,t) - g(x_2,u,t)\| \le \lambda \|x_1 - x_2\|, \forall u, t, \tag{8}$$

where λ is the Lipschitz constant.

The control objective of this paper is as follows: if there is no fault, outputs $y = z$ should be regulated to achieve their given set-points y_r; if a fault occurs and it is identifiable, the control objective is to regulate z to track set-points y_r; if a non-identifiable fault occurs, only the unpolluted outputs are regulated to track the given set-points.

3. FAULT DETECTION AND ISOLATION

To achieve the control objective, an FDI module should be designed first to detect the fault, to isolate which sensor has fault, to judge whether the fault is identifiable.

Firstly, a fault detection observer (FDO) is introduced in the follows:

$$\dot{\bar{x}}(t) = A\bar{x}(t) + Bu + g(\bar{x},u,t) + \bar{L}(C\bar{x} - y). \quad (9)$$

Let the error vector be defined as

$$e_x(t) \triangleq \bar{x}(t) - x(t). \quad (10)$$

From (1), (9) and (10), it can be obtained that

$$\dot{e}_x(t) = (A + \bar{L}C)e_x(t) + (g(\bar{x},u,t) - g(x,u,t)). \quad (11)$$

The following lemma gives a sufficient condition for (11) being stable.

Lemma 1: Estimation error e_x converges asymptotically to zero if there exist matrices $R = R^T > 0$, X and positive scalar $\mu > 0$ such that the following linear matrix inequality (LMI) is satisfied:

$$\begin{bmatrix} RA + A^T R + XC + C^T X^T + \mu\lambda^2 I & R \\ R & -\mu I \end{bmatrix} < 0. \quad (12)$$

The observer gain matrix can be selected as

$$\bar{L} = R^{-1}X. \quad (13)$$

Proof: Consider the following Lyapunov function

$$V(t) = e_x^T(t)Re_x(t). \quad (14)$$

Computing $\dot{V}(t)$ along the trajectory of (11) yields

$$\begin{aligned} \dot{V} &= e_x^T\left(RA + R\bar{L}C + A^T R + C^T \bar{L}^T R\right)e_x \\ &\quad + 2e_x^T R\left(g(\bar{x},u,t) - g(x,u,t)\right) \\ &\le e_x^T\left(RA + R\bar{L}C + A^T R + C^T \bar{L}^T R\right)e_x \\ &\quad + \tfrac{1}{\mu} e_x^T R^2 e_x + \mu\|g(\bar{x},u,t) - g(x,u,t)\|^2 \quad (15) \\ &\le e_x^T\left(RA + R\bar{L}C + A^T R + C^T \bar{L}^T R\right)e_x \\ &\quad + \tfrac{1}{\mu} e_x^T R^2 e_x + \mu\lambda^2\|e_x\|^2 \\ &= e_x^T \begin{pmatrix} RA + R\bar{L}C + A^T R \\ +C^T \bar{L}^T R + \mu\lambda^2 I + \tfrac{1}{\mu}R^2 \end{pmatrix} e_x. \end{aligned}$$

Substituting (13) into (15), it can be further obtained that

$$\begin{aligned} \dot{V} \le e_x^T(&RA + XC + A^T R + C^T X^T \\ &+ \mu\lambda^2 I + \tfrac{1}{\mu}R^2)e_x. \end{aligned} \quad (16)$$

If the following inequality

$$RA + XC + A^T R + C^T X^T + \mu\lambda^2 I + \tfrac{1}{\mu}R^2 < 0 \quad (17)$$

holds, e_x converges asymptotically to zero. From the Schur complement, (17) is equivalent to (12). This completes the proof. □

Similarly, the following theorem can be readily obtained.

Theorem 1: If there exist matrices $R = R^T > 0$, X and positive scalars $\mu > 0$ and $\kappa > 0$ such that the following inequality is satisfied:

$$\begin{bmatrix} RA + A^T R + XC + C^T X^T + \mu\lambda^2 I + \kappa R & R \\ R & -\mu I \end{bmatrix} < 0 \quad (18)$$

and let

$$\bar{L} = R^{-1}X \quad (19)$$

then, estimation error e_x converges exponentially to zero with rate $\kappa/2 > 0$.

Proof: Similar to the proof of Lemma 1, from (18) and (16), it can be obtained that

$$\dot{V}(t) \le -\kappa e_x^T R e_x = -\kappa V(t). \quad (20)$$

Hence,

$$V(t) \le e^{-\kappa t}V(0). \quad (21)$$

From (14), it can be obtain that

$$\lambda_{\min}(R)\|e_x(t)\|^2 \le e^{-\kappa t}\lambda_{\max}(R)\|e_x(0)\|^2, \quad (22)$$

where $\lambda_{\min}(R)$ and $\lambda_{\max}(R)$ denote the minimum and maximum eigenvalues of matrix R respectively. Therefore the nom of the error vector satisfies

$$\|e_x(t)\| \le \sqrt{\lambda_{\max}(R)/\lambda_{\min}(R)}\,\|e_x(0)\|e^{-\kappa t/2}. \quad (23)$$

This finished the proof.

From (9) and (1), the detection residual can be defined as

$$r(t) \triangleq \|C\bar{x}(t) - y(t)\|. \quad (24)$$

From (10) and (23), it can be seen that the following inequality holds in healthy case:

$$r(t) \le \sqrt{\lambda_{\max}(R)/\lambda_{\min}(R)}\,\|C\|\|e_x(0)\|e^{-\kappa t/2}. \quad (25)$$

Note that $\|e_x(0)\|$ is unknown generally, so the threshold in (25) is unavailable. However, since it can be shown that $\|C\|\|e_x(0)\| \approx \|r(0)\|$, the fault detection can be performed using the following mechanism:

$$r(t)\begin{cases} \le \sqrt{\lambda_{\max}(R)/\lambda_{\min}(R)}\,\|r(0)\|e^{-\kappa t/2}, \textit{ there is no fault} \\ > \sqrt{\lambda_{\max}(R)/\lambda_{\min}(R)}\,\|r(0)\|e^{-\kappa t/2}, \textit{ there is a fault.} \end{cases} \tag{26}$$

Notice that matrix inequality (18) is not an LMI and is therefore difficult to solve. The following algorithm is proposed here to solve this inequality:

Algorithm 1:

1) Solve LMI (12) and obtain $R > 0$, X and $\mu > 0$. Then R, X and μ are fixed and let $\kappa = 0$.
2) Let $\kappa = \kappa + \Delta\kappa$.
3) Solve (18): if solvable, go to 2); else, go to 4).
4) $\kappa = \kappa - \Delta\kappa$. Exit,

where $\Delta\kappa > 0$ is the designed search step.

Remark 1: It is worthwhile to point out that uncertainties were not considered in fault detection scheme (26). In fact, there are many literatures about robust fault detection (for example [17-19]). Since fault detection is not the emphasis of this paper, a simple fault detection threshold is chosen as

$$\varepsilon(t) \triangleq \vartheta\sqrt{\lambda_{\max}(R)/\lambda_{\min}(R)}\,\|r(0)\|e^{-\kappa t/2} + \eta, \tag{27}$$

where $\vartheta > 1$ and $\eta > 0$ is determined by the magnitude of uncertainties.

Because any sensor fault can affect all estimation errors simultaneously, the above observer and scheme are only used for fault detection. In the following, some observers will be designed to isolate sensor faults. For this purpose, define $\tilde{C}_i \triangleq C \setminus C_i$, i.e., it is the remaining part of matrix C with by omitting its row vector C_i. Similarly to (9) and (10), we can design m isolation observers as follows,

$$\Xi_i : \begin{cases} \dot{\bar{x}}_i(t) = A\bar{x}_i(t) + Bu + g(\bar{x}_i, u, t) + \bar{L}_i(\tilde{C}_i\bar{x}_i - \tilde{y}_i) \\ e_{xi}(t) \triangleq \bar{x}_i(t) - x(t), \end{cases} \quad i = 1, \cdots, m \tag{28}$$

where

$$\tilde{y}_i \triangleq y \setminus y_i,\ i = 1, \cdots, m. \tag{29}$$

From Lemma 1, it is obtained that if LMI

$$\begin{bmatrix} R_iA + A^TR_i + X_i\tilde{C}_i + \tilde{C}_i^TX_i^T + \mu_i\lambda^2 I & R_i \\ R_i & -\mu_i I \end{bmatrix} < 0 \tag{30}$$

holds, with the observer gain matrices being determined by

$$\bar{L}_i = R_i^{-1}X_i, \tag{31}$$

then e_{xi} converges asymptotically to zero.

It is easy to prove that a necessary condition for (30) is $(A, \tilde{C}_i)$ being detectable.

From Theorem 1, it is obtained that if LMI

$$\begin{bmatrix} R_iA + A^TR_i + X_i\tilde{C}_i + \tilde{C}_i^TX_i^T + \mu_i\lambda^2 I + \kappa_iR_i & R_i \\ R_i & -\mu_i I \end{bmatrix} < 0 \tag{32}$$

then, estimation error e_{xi} converges exponentially to zero with rate $\kappa_i/2 > 0$. Therefore, if there is no fault, then

$$\begin{aligned} r_i(t) &\triangleq \|C_i\bar{x}_i(t) - y_i(t)\| \\ &\le \sqrt{\lambda_{\max}(R_i)/\lambda_{\min}(R_i)}\,\|C_i\|\|e_{xi}(0)\|e^{-\kappa_i t/2} \end{aligned} \tag{33}$$

and

$$\begin{aligned} \tilde{r}_i(t) &\triangleq \|\tilde{C}_i\bar{x}_i(t) - \tilde{y}_i(t)\| \\ &\le \sqrt{\lambda_{\max}(R_i)/\lambda_{\min}(R_i)}\,\|\tilde{C}_i\|\|e_{xi}(0)\|e^{-\kappa_i t/2}. \end{aligned} \tag{34}$$

Assume that there is a fault in sensor *i* and there is no fault in other sensors. Since y_i is not used in Ξ_i, so inequality (34) is still true whilst (33) does not hold. Hence, the isolation law for sensor *i* can be designed as

$$\text{if } \begin{cases} r_i(t) > \vartheta_i\sqrt{\lambda_{\max}(R_i)/\lambda_{\min}(R_i)}\,\|r_i(0)\|e^{-\kappa_i t/2} + \eta_i \\ \tilde{r}_i(t) \le \vartheta_i\sqrt{\lambda_{\max}(R_i)/\lambda_{\min}(R_i)}\,\|\tilde{r}_i(0)\|e^{-\kappa_i t/2} + \eta_i, \end{cases} \tag{35}$$

then there is a fault in sensor *i*.

4. FAULT DIAGNOSIS

According to the fault detection and isolation results in the above section, we have obtained that whether there exist faults and which sensor has a fault. Assume that there is a fault in sensor i, an observer should be designed to estimate this fault and the real value of the polluted output. The ith output can be described as:

$$y_i(t) = C_ix(t) + f_i(x, t). \tag{36}$$

Rewriting the system description (1) by taking into account (36), we obtain

$$\begin{cases} \dot{x}(t) = Ax(t) + g(x, u, t) + Bu(t) \\ y(t) = Cx(t) + D_if_i(x, t), \end{cases} \tag{37}$$

where it has been denoted that

$$D_i = \begin{bmatrix} 0 & \cdots & 0 & \underset{i}{1} & 0 & \cdots & 0 \end{bmatrix}^T. \tag{38}$$

To use the observer presented in [16], matrix D_i should satisfy the following equation:

$$rank\begin{bmatrix} \mu I - A & 0 \\ C & D_i \end{bmatrix} = n + rankD_i, \tag{39}$$
$$\forall \mu \in C^+ \text{(closed right-half plane)}.$$

Denote

$$\begin{cases} E = [I_n \quad 0_{n\times 1}] \\ M = [A \quad 0_{n\times 1}] \\ H_i = [C \quad D_i] \\ \zeta_i = \begin{pmatrix} x \\ f_i \end{pmatrix}. \end{cases} \tag{40}$$

Let

$$\begin{bmatrix} P_i & Q_i \end{bmatrix} = \left(\begin{bmatrix} E \\ H_i \end{bmatrix}^T \begin{bmatrix} E \\ H_i \end{bmatrix} \right)^{-1} \begin{bmatrix} E \\ H_i \end{bmatrix}^T, \tag{41}$$

where $P_i \in \mathbb{R}^{(n+1)\times n}, Q_i \in \mathbb{R}^{(n+1)\times m}$.

Construct the unknown-input observer as follows:

$$\begin{cases} \dot{z}_i = N_i z_i + L_i y + P_i B u + P_i g(\hat{x}_i, u, t), \\ \hat{\zeta}_i = z_i + Q_i y, \end{cases} \tag{42}$$

where $z_i \in \mathbb{R}^{n+1}$. Let

$$\zeta_i \triangleq \begin{pmatrix} x \\ f_i \end{pmatrix}, \hat{\zeta}_i \triangleq \begin{pmatrix} \hat{x}_i \\ \hat{f}_i \end{pmatrix}, \tag{43}$$

$$e_i = \hat{\zeta}_i - \zeta_i = \begin{pmatrix} \hat{x}_i - x \\ \hat{f}_i - f_i \end{pmatrix} \triangleq \begin{pmatrix} \tilde{x}_i \\ \tilde{f}_i \end{pmatrix}. \tag{44}$$

It is valuable to point out that $\hat{x}_i$ denotes the estimation of x produced by the i th observer.

From [16], we obtain

$$\begin{aligned} \dot{e}_i = N_i e_i + (N_i + F_i H_i - P_i M)\zeta_i \\ + P_i(g(\hat{x}_i, u, t) - g(x, u, t)), \end{aligned} \tag{45}$$

where

$$F_i \triangleq L_i - N_i Q_i. \tag{46}$$

Let

$$N_i \triangleq P_i M - F_i H_i, \tag{47}$$

then (45) can be further expressed as

$$\dot{e}_i = (P_i M - F_i H_i)e_i + P_i(g(\hat{x}_i, u, t) - g(x, u, t)). \tag{48}$$

Lemma 2 [16]**:** Assume that system (1) satisfies Assumptions 2 and 3. The estimation error e_i of observer (48) converges asymptotically to zero if there exist matrices $R_i = R_i^T > 0$, X_i and positive scalars $\mu_i > 0$ such that the following LMI is satisfied:

$$\Omega_i \triangleq \begin{bmatrix} R_i P_i M + M^T P_i^T R_i - X_i H_i - H_i^T X_i^T + \mu_i \lambda^2 I & R_i P_i \\ P_i^T R_i & -\mu_i I \end{bmatrix} < 0. \tag{49}$$

where λ is the Lipschitz constant defined in (8). Let

$$F_i \triangleq R_i^{-1} X_i. \tag{50}$$

From (50), (47) and (46), we can obtain N_i and L_i.

By using (49), we can judge whether the fault can be estimated. If $\Omega_i < 0$ is solvable, then sensor i is said to be identifiable sensor, and a fault in this sensor is called identifiable fault. Otherwise, sensor i is called non-identifiable sensor and its fault is called non-identifiable fault. For each identifiable sensor, an unknown-input observer (42) is designed correspondingly. Since $y \in \mathbb{R}^m$, at most m estimation observers should be designed. In the following section, different control schemes will be designed for different classes of sensor faults.

5. CONTROLLER DESIGN

Generally speaking, m outputs could be regulated by using m inputs. Hence, the following assumption is made.

Assumption 4: It is assumed that $p = m$, and matrix CB is nonsingular.

That is to say, the considered system is a multi-input and multi-output nonlinear square system. Most industrial processes are designed to be open-loop stable; that is to say, the outputs must be bounded when the system is subjected to bounded inputs. On the other hand, due to some physical limitations, the system states are bounded by some known boundary. Hence, it is also reasonable to introduce the following assumption:

Assumption 5: In all cases, system states are bounded, i.e.,

$$\|x\| \leq \Sigma, \tag{51}$$

where $\Sigma > 0$ is a known constant.

Assume that the set-point of the output is y_r, then, it is intuitive to choose the sliding mode as

$$s(t) \triangleq Cx(t) - y_r. \tag{52}$$

Since C is of a full row rank, there must exist a matrix $\bar{C} \in \mathbb{R}^{(n-p)\times n}$ such that matrix

$$T \triangleq \begin{bmatrix} C \\ \bar{C} \end{bmatrix} \tag{53}$$

is nonsingular. Correspondingly, the inverse matrix of T is defined as

$$T^{-1} \triangleq \begin{bmatrix} T_1 & T_2 \end{bmatrix}. \tag{54}$$

From (1), (52), (53) and (54), we obtain

$$\begin{aligned} \dot{s}(t) &= CAx(t) + Cg(x,u,t) + CBu(t) \\ &= CAT^{-1}Tx(t) + Cg(T^{-1}Tx,u,t) + CBu(t) \\ &= CA\begin{bmatrix} T_1 & T_2 \end{bmatrix}\begin{bmatrix} C \\ \bar{C} \end{bmatrix}x \\ &\quad + Cg\left(\begin{bmatrix} T_1 & T_2 \end{bmatrix}\begin{bmatrix} C \\ \bar{C} \end{bmatrix}x,u,t\right) + CBu(t) \\ &= CAT_1 s(t) + CAT_1 y_r + CAT_2\bar{C}x \\ &\quad + Cg\left(T_1 s + T_1 y_r + T_2\bar{C}x,u,t\right) + CBu(t). \end{aligned} \tag{55}$$

From the above statement, we can design the control law as the following form:

$$\begin{aligned} u &= -(CB)^{-1}CAT_1 s - \alpha(CB)^{-1}s \\ &\quad -(CB)^{-1}\begin{bmatrix} \|CAT_1 y_r\| + \|CAT_2\bar{C}\|\mathrm{X} + \|C\|\|g(T_1 s,u,t)\| \\ +\lambda\|C\|\|T_1 y_r\| + \lambda\|C\|\|T_2\bar{C}\|\mathrm{X} \end{bmatrix}\mathrm{sgn}(s), \end{aligned} \tag{56}$$

where $\alpha > 0$ and

$$\mathrm{sgn}(s) \triangleq \begin{bmatrix} \mathrm{sgn}(s_1) & \mathrm{sgn}(s_2) & \cdots & \mathrm{sgn}(s_p) \end{bmatrix}^T. \tag{57}$$

Obviously, we have

$$s^T \mathrm{sgn}(s) = \|s\|. \tag{58}$$

Theorem 2: Under control law (56), the output of the closed-loop system convergences to the sliding-mode surface $s = 0$ asymptotically.

Proof: Define

$$W(t) = \frac{1}{2}s^T s \tag{59}$$

then, from (55), it can be formulated that

$$\begin{aligned} \dot{W} &= s^T\dot{s} = s^T\begin{bmatrix} CAT_1 s + CAT_1 y_r + CAT_2\bar{C}x \\ +Cg\left(T_1 s + T_1 y_r + T_2\bar{C}x,u,t\right) + CBu \end{bmatrix} \\ &\le s^T CAT_1 s + \|s\|\|CAT_1 y_r\| + \|s\|\|CAT_2\bar{C}\|\Sigma \\ &\quad + \|s\|\|C\|\left\|g\left(T_1 s + T_1 y_r + T_2\bar{C}x,u,t\right)\right\| + s^T CBu. \end{aligned} \tag{60}$$

From Assumption 3, the following inequality should hold true.

$$\begin{aligned} &\left\|g\left(T_1 s + T_1 y_r + T_2\bar{C}x,u,t\right)\right\| \\ &\quad \le \left\|g\left(T_1 s,u,t\right)\right\| + \lambda\|T_1 y_r\| + \lambda\|T_2\bar{C}\|\mathrm{X} \end{aligned} \tag{61}$$

Combining (60) with (61), (56) and (58), it can be obtained that

$$\dot{W} \le -\alpha s^T s. \tag{62}$$

This completes the proof. □

From Theorem 2 and (52), we obtain that the outputs convergence to their set-points asymptotically.

In designing sliding mode control law (56), it is assumed that the control can switch infinitely fast. This is infeasible due to speed limitations on actuators. The non-ideal switching can result in chattering phenomenon. To eliminate this undesirable chattering, it is practical to replace the sign function by a saturation function, $sat_\mu(s)$, which is defined by

$$\begin{aligned} &sat_\mu(s) \triangleq \begin{bmatrix} sat_\mu(s_1) & sat_\mu(s_2) & \cdots & sat_\mu(s_p) \end{bmatrix}^T, \\ &sat_\mu(s_i) \triangleq \begin{cases} s_i/\mu, & if\ |s_i/\mu| < 1 \\ \mathrm{sgn}(s_i/\mu), & if\ |s_i/\mu| \ge 1, \end{cases} \quad i = 1,\cdots,p. \end{aligned} \tag{63}$$

Theorem 3: Under the following control law

$$\begin{aligned} u &= -(CB)^{-1}CAT_1 s - \alpha(CB)^{-1}s \\ &\quad -(CB)^{-1}\begin{bmatrix} \|CAT_1 y_r\| + \|CAT_2\bar{C}\|\Sigma + \lambda\|C\|\|T_1 y_r\| \\ +\lambda\|C\|\|T_2\bar{C}\|\Sigma + \|C\|\|g(T_1 s,u,t)\| \end{bmatrix} sat_\mu(s) \end{aligned} \tag{64}$$

the closed-loop system convergences to boundary layer $|s| \le \mu$ ultimately. In other words, sliding mode $s(t)$ is ultimately uniformly bounded.

Proof: From the proof of Theorem 2 and (63), we obtain that $\dot{W} \le -\alpha s^T s$ if $|s/\mu| \ge 1$. Hence, $s(t)$ convergences to boundary layer $|s| \le \mu$ ultimately.

If there is a fault in identifiable sensor i $(i = 1,\cdots,p)$, then, observer (42) is used to estimate the states and fault. It is reasonable to design the fault-tolerant control law as the following form:

$$\begin{aligned} u &= -(CB)^{-1}CAT_1\hat{s}_i - \alpha(CB)^{-1}\hat{s}_i \\ &\quad -(CB)^{-1}\begin{bmatrix} \|CAT_1 y_r\| + \|CAT_2\bar{C}\|\Sigma + \lambda\|C\|\|T_1 y_r\| \\ +\|C\|\|g(T_1\hat{s}_i,u,t)\| + \lambda\|C\|\|T_2\bar{C}\|\Sigma \end{bmatrix} sat_\mu(\hat{s}_i), \end{aligned} \tag{65}$$

where

$$\hat{s}_i \hat{=} \begin{bmatrix} s_1 & \cdots & s_{i-1} & C_i\hat{x}_i - y_r^i & s_{i+1} & \cdots & s_p \end{bmatrix}^T. \tag{66}$$

For this fault tolerant control law, the following result can be obtained

Theorem 4: Under control law (65), the closed-loop system convergences to boundary layer $|s| \le \mu$ ultimately.

Proof: From (59), (60), (61), (63), and (65), we obtain that if $|s| \ge \mu$, then

$$\begin{aligned} \dot{W} \le & -\alpha s^T s + s^T CAT_1\tilde{s}_i + \alpha s^T \tilde{s}_i \\ & + s^T \|C\| [\|g(T_1 s,u,t)\| sat_\mu(s) \\ & \quad - \|g(T_1\hat{s}_i,u,t)\| sat_\mu(\hat{s}_i)] \\ & + s^T [\|CAT_1 y_r\| + \|CAT_2\bar{C}\|\Sigma \\ & \quad + \lambda\|C\|\|T_1 y_r\| + \lambda\|C\|\|T_2\bar{C}\|\Sigma] \\ & \quad \times [sat_\mu(s) - sat_\mu(\hat{s}_i)], \end{aligned} \tag{67}$$

where $\tilde{s}_i \hat{=} s - \hat{s}_i$. From Lemma 2 and (66), it can shown that

$$\lim_{t\to\infty} \|\tilde{s}_i(t)\| = 0. \tag{68}$$

From Assumption 3 and (63), we obtain that $\|g(T_1 s,u,t)\| sat_\mu(s) - \|g(T_1\hat{s}_i,u,t)\| sat_\mu(\hat{s}_i)$ and $sat_\mu(s) - sat_\mu(\hat{s}_i)$ convergence to zeros as $\|\tilde{s}_i(t)\|$ convergences to zero. On the other hand, from Assumption 5, we know that s is bounded. Therefore, there is a $T > 0$ such that if $t \ge T$ and $|s| \ge \mu$

$$\begin{aligned} & \left\| \begin{aligned} & s^T CAT_1\tilde{s}_i + \alpha s^T \tilde{s}_i + s^T \|C\| \left[\|g(T_1 s,u,t)\| sat_\mu(s) \right. \\ & \left. - \|g(T_1\hat{s}_i,u,t)\| sat_\mu(\hat{s}_i) \right] + s^T \left[\|CAT_1 y_r\| + \|CAT_2\bar{C}\|\Sigma \right. \\ & \left. + \lambda\|C\|\|T_1 y_r\| + \lambda\|C\|\|T_2\bar{C}\|\Sigma \right] \times \left[sat_\mu(s) - sat_\mu(\hat{s}_i) \right] \end{aligned} \right\| \\ & \quad \le \frac{1}{2}\alpha\mu^2 \le \frac{1}{2}\alpha s^T s. \end{aligned} \tag{69}$$

Combining (67) and (69), it can be shown that the following inequality

$$\dot{W} \le -\frac{1}{2}\alpha s^T s < 0 \tag{70}$$

holds, if $t \ge T$ and $|s| \ge \mu$. Hence, W will decrease, and then $s(t)$ will decrease until it convergences to boundary layer $|s| \le \mu$ ultimately. This finishes the proof.

If there is a fault in non-identifiable sensor i $(i = 1, \cdots, p)$, then we cannot design an estimate observer. Hence, the control objective should be released. For this purposed, define

$$\tilde{C}_i \hat{=} \begin{bmatrix} C_1 \\ \vdots \\ C_{i-1} \\ C_{i+1} \\ \vdots \\ C_p \end{bmatrix}, \quad \tilde{y}_{ri} \hat{=} \begin{bmatrix} y_r^1 \\ \vdots \\ y_r^{i-1} \\ y_r^{i+1} \\ \vdots \\ y_r^p \end{bmatrix}, \quad s_i \hat{=} \tilde{C}_i x - \tilde{y}_{ri}. \tag{71}$$

From Assumption 4, it can be seen that there exist $j_i \in \{1, 2, \cdots, p\}$, such that $\tilde{C}_i \tilde{B}_{j_i}$ is nonsingular, where

$$\tilde{B}_{j_i} \hat{=} \begin{bmatrix} B_1 & \cdots & B_{j_i-1} & B_{j_i+1} & \cdots & B_p \end{bmatrix}. \tag{72}$$

Notice that

$$Bu = \tilde{B}_{j_i}\tilde{u}_{j_i} + B_{j_i} u_{j_i},$$

where

$$\tilde{u}_{j_i} \hat{=} \begin{bmatrix} u_1 & \cdots & u_{j_i-1} & u_{j_i+1} & \cdots & u_p \end{bmatrix}^T. \tag{73}$$

Assume that the non-identifiable fault is isolated at time $T_{isolate}$, then it is reasonable to choose the j_i th control law as

$$u_{j_i} \equiv u_{j_i}(T_{isolate}). \tag{74}$$

Then, similarly to (64), we can design the fault-tolerant control law as

$$\begin{aligned} \tilde{u}_{j_i} = & -(\tilde{C}_i\tilde{B}_{j_i})^{-1}\tilde{C}_i AT_{1i} s_i - \alpha(\tilde{C}_i\tilde{B}_{j_i})^{-1} s_i \\ & -(\tilde{C}_i\tilde{B}_{j_i})^{-1} sat_\mu(s_i) \\ & \times \begin{bmatrix} \|\tilde{C}_i AT_{1i} y_r\| + \|\tilde{C}_i AT_{2i}\bar{\tilde{C}}_i\|\Sigma + \|\tilde{C}_i\|\|g(T_{1i}s_i,u,t)\| \\ +\lambda\|\tilde{C}_i\|\|T_{1i} y_r\| + \lambda\|\tilde{C}_i\|\|T_{2i}\bar{\tilde{C}}_i\|\Sigma + \|\tilde{C}_i B_{j_i} u_{j_i}\| \end{bmatrix}, \end{aligned} \tag{75}$$

where $\begin{bmatrix} \tilde{C}_i \\ \bar{\tilde{C}}_i \end{bmatrix}$ is nonsingular and

$$\begin{bmatrix} T_{1i} & T_{2i} \end{bmatrix} \begin{bmatrix} \tilde{C}_i \\ \bar{\tilde{C}}_i \end{bmatrix} = I. \tag{76}$$

Theorem 5: Under control law (75), the closed-loop system convergences to boundary layer $|s_i| \le \mu$ ultimately.

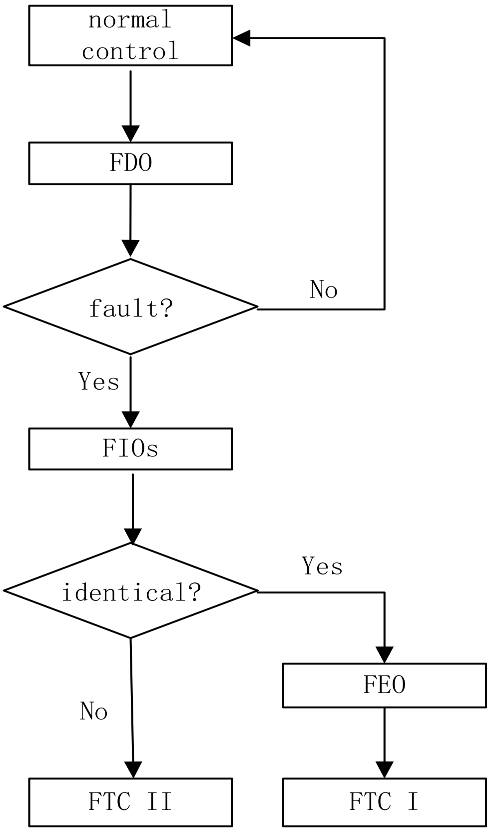

Fig. 1. Block diagram of the proposed scheme.

Proof: The proof is similar to that of Theorem 3, and is omitted here.

In this section, two kinds of fault-tolerant control laws were designed for identifiable and non-identifiable faults respectively. For convenience, control law (65) is named FTC I, whilst control law (74) and (75) is named FTC II. To summarize the controllers, the block diagram of the proposed scheme is shown in Fig. 1.

6. SIMULATION STUDY

In this section, the following example is studied

$$A=\begin{bmatrix}-2 & 1 & 0\\ 0 & -1 & 1\\ 0 & 0 & -1\end{bmatrix}, B=I_3, C=I_3, g=0.8\times\begin{bmatrix}\sin x_3\\ \cos x_2\\ \sin x_1\end{bmatrix}.$$

Solving LMI (12), it can be obtained that

$$\bar{L}=\begin{bmatrix}\text{-0.7150} & 0.8420 & \text{-35.3886}\\ \text{-1.8420} & \text{-1.7150} & \text{-79.0740}\\ 35.3886 & 78.0740 & \text{-2.2150}\end{bmatrix},$$

$$R=\begin{bmatrix}10.1542 & 0 & 0\\ 0 & 10.1542 & 0\\ 0 & 0 & 10.1542\end{bmatrix}.$$

Let $\Delta\kappa=0.01$ and use Algorithm 1, then we obtain that $\kappa=2.66$. The detection threshold is chosen as in (27), where $\vartheta=2$ and $\eta=0.5$.

Solving LMI (30) and using Algorithm 1, we obtain that

$$\bar{L}_1=\begin{bmatrix}\text{-1.0000} & 0\\ \text{-1.6969} & \text{-82.7877}\\ 81.7877 & \text{-2.1969}\end{bmatrix},$$

$$\bar{L}_2=\begin{bmatrix}\text{-1.1504} & \text{-52.3676}\\ \text{-1.4511} & \text{-11.9846}\\ 48.3983 & \text{-2.1261}\end{bmatrix},$$

$$\bar{L}_3=\begin{bmatrix}\text{-0.0440} & \text{-106.1783}\\ 145.4842 & \text{-2.6692}\\ 84.7751 & \text{-2.6742}\end{bmatrix},$$

$$R_1=\begin{bmatrix}12.9899 & 0 & 0\\ 0 & 10.0428 & 0\\ 0 & 0 & 10.0428\end{bmatrix}, \kappa_1=1.71,$$

$$R_2=\begin{bmatrix}9.0098 & \text{-3.2557} & 0\\ \text{-3.2557} & 15.5213 & 0\\ 0 & 0 & 9.0098\end{bmatrix}, \kappa_2=0.39,$$

$$R_3=\begin{bmatrix}0.4186 & 0 & 0\\ 0 & 0.4840 & \text{-0.3112}\\ 0 & \text{-0.3112} & 0.5340\end{bmatrix}, \kappa_3=0.05.$$

Solving LMI (49) for three sensors respectively, it is obtained that

$$N_1=\begin{bmatrix}\text{-1.4430} & \text{-1.7896} & 0.1280 & 0.5570\\ 2.6844 & \text{-1.3290} & 0.2304 & 2.6844\\ \text{-0.1921} & \text{-0.2304} & \text{-1.3290} & \text{-0.1921}\\ 0.5570 & \text{-1.7896} & 0.1280 & \text{-1.4430}\end{bmatrix},$$

$$L_1=\begin{bmatrix}0 & 1.8948 & \text{-0.0640}\\ 0 & 0.1645 & 0.3848\\ 0 & 0.1152 & 0.4145\\ 0 & \text{-0.1052} & \text{-0.0640}\end{bmatrix},$$

$$P_1=\begin{bmatrix}1 & 0 & 0\\ 0 & 0.5 & 0\\ 0 & 0 & 0.5\\ -1 & 0 & 0\end{bmatrix}, \quad Q_1=\begin{bmatrix}0 & 0 & 0\\ 0 & 0.5 & 0\\ 0 & 0 & 0.5\\ 1 & 0 & 0\end{bmatrix},$$

and

$$N_2=\begin{bmatrix}\text{-3.0817} & \text{-1.8939} & 0.0661 & \text{-2.3939}\\ \text{-1.9868} & \text{-2.8766} & 2.7964 & \text{-1.8766}\\ \text{-0.0514} & \text{-3.9756} & \text{-1.2841} & \text{-3.9756}\\ 4.2809 & 2.0680 & 2.6749 & 1.0680\end{bmatrix},$$

$$L_2 = \begin{bmatrix} 0.5408 & 0 & -0.0330 \\ 0.9934 & 0 & -0.3982 \\ 0.0257 & 0 & 0.3921 \\ -2.1405 & 0 & -2.3374 \end{bmatrix},$$

$$P_2 = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.5 \\ 0 & -1 & 0 \end{bmatrix}, \quad Q_2 = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0.5 \\ 0 & 1 & 0 \end{bmatrix},$$

however $\Omega_3 < 0$ is unsolvable, that is to say, sensor 3 is non-identifiable sensor.

Then, the normal control law, FTC I and FTC II can be designed as (64), (65) and (74), (75) respectively, where $\alpha = 0.5$, $\Sigma = 50$ and $\mu = 0.5$. To demonstrate the effectiveness of the proposed method sufficiently, three kinds of sensor faults are studied in the following.

Case 1: Bias Fault in Sensor 1.

In this case, the measured outputs are assumed to be

$$y(t) = \begin{cases} z(t), & 0 \le t < 5 \\ z(t) + \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix}, & t \ge 5. \end{cases}$$

The output responses under FTC and normal control are shown in Fig. 2, which indicates that the proposed method can tolerate this fault excellently while the normal one cannot. The fault detection result is shown in Fig. 3(a), and it is found that the fault can be detected immediately after 5 second. The estimation results of isolation observer 1 is shown in Figs. 3(b) and (c). From (35), we can judge that the fault is in sensor 1, so the corresponding control law can be activated then.

Case 2: Gain Fault in Sensor 2.

The measured outputs are

$$y(t) = \begin{cases} z(t), & 0 \le t < 5 \\ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.8 & 0 \\ 0 & 0 & 1 \end{bmatrix} z(t), & t \ge 5. \end{cases}$$

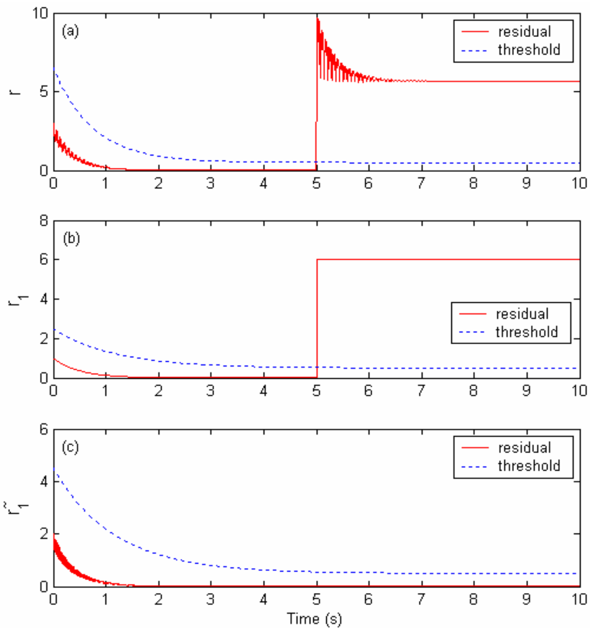

Fig. 3. Fault detection and isolation for fault in sensor 1.

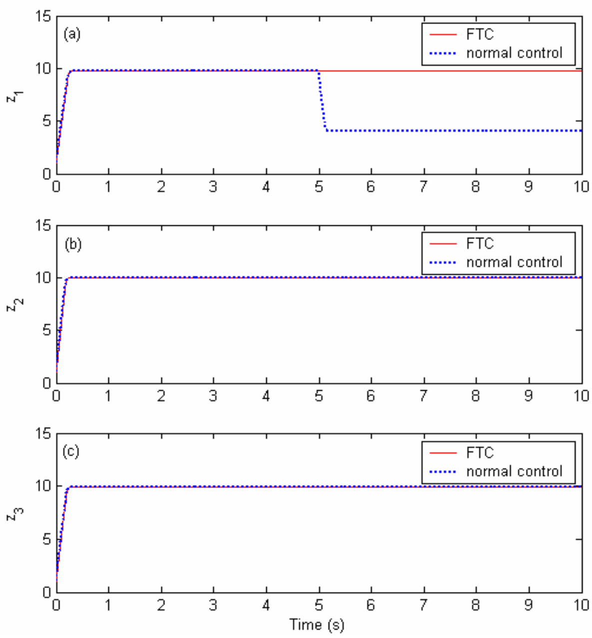

Fig. 2. Comparison of FTC and normal control with fault in sensor 1.

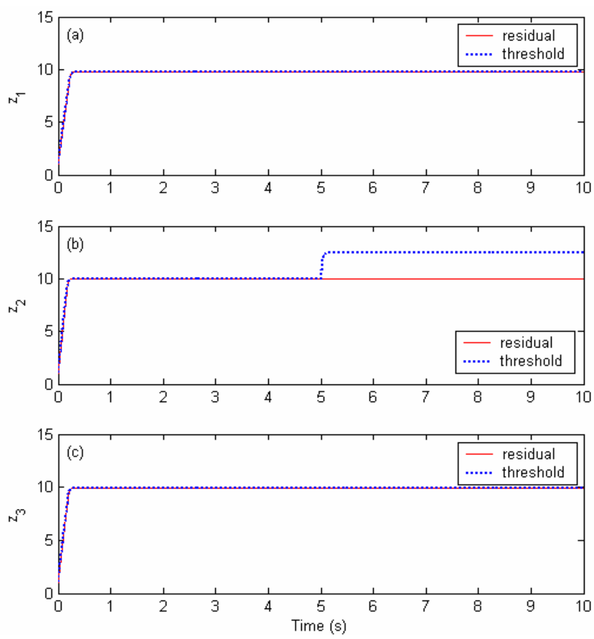

Fig. 4. Comparison of FTC and normal control with fault in sensor 2.

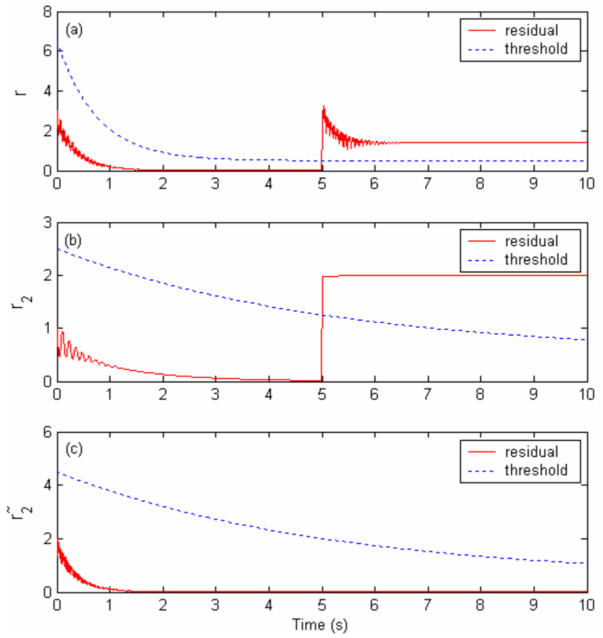

Fig. 5. Fault detection and isolation for fault in sensor 2.

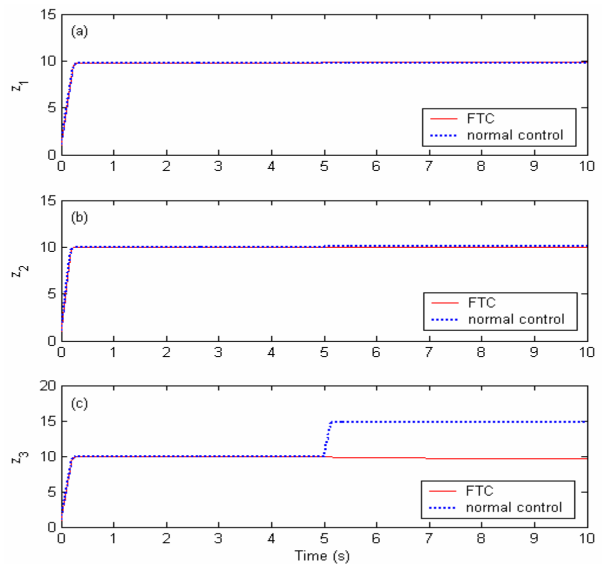

Fig. 6. Comparison of FTC and normal control with fault in sensor 3.

The output responses are shown in Fig. 4. The fault detection and isolation results are given in Fig. 5.

Case 3: Bias Fault in Sensor 3.

In this case, the measured outputs are

$$y(t)=\begin{cases} z(t), & 0 \le t < 5 \\ z(t)+\begin{bmatrix}0 & 0 & -5\end{bmatrix}^T, & t \ge 5. \end{cases}$$

From Fig. 6(c), we can find that the control performance of z_3 descends evidently under normal control law but slightly under FTC II. The fault detection and isolation results are shown in Fig. 7.

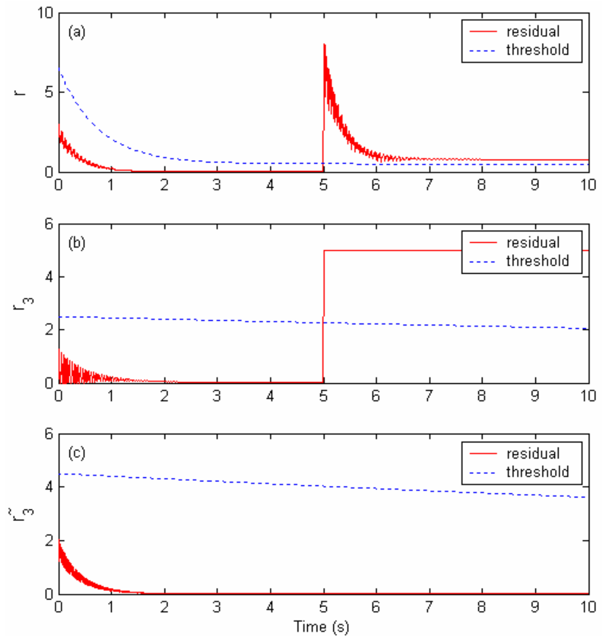

Fig. 7. Fault detection and isolation for fault in sensor 3.

7. CONCLUSIONS

By designing one detection observer for all outputs and presenting an isolation observer and an estimation observer for each output, an active fault-tolerant control framework has been proposed for a class of nonlinear systems with sensor faults. If an identifiable fault occurs, the closed-loop system under fault-tolerant control has a similar control performance compared with that in the healthy case. If a non-identifiable fault occurs, the closed-loop control performance has a little degradation. A simulated example is included to show the effectiveness of the proposed algorithms and encouraging results have been obtained.

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