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ToMFIR-based Detection and Estimation for Incipient Actuator Faults in a class of Closed-Loop Nonlinear Systems

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Abstract: Since incipient faults often have small amplitudes and obscure symptoms, those observer-based or output residual-based fault indicators are ineffective for incipient faults, especially in the presence of system disturbances. The ToMFIR-based fault detection approaches use both controller and output residuals to construct a fault indicator, which make them sensitive to incipient faults. This paper extends the ToMFIR-based fault detection approaches to a class of closed-loop nonlinear systems under the consideration of system disturbances. The restriction on the fault type is removed compared with the existing approaches, and ToMFIR-based fault estimation algorithm has been derived. Verification results in a near space hypersonic vehicle (NSHV) simulation system can demonstrate the effectiveness of the proposed approach.

Keywords: Total measurable fault information residual (ToMFIR); Closed-loop nonlinear system; Fault detection and estimation (FDE); Incipient fault.

1. INTRODUCTION

Most of model-based fault detection techniques rely on a variety of residual-based fault indicators, where "residuals" are typically defined as the differences between the measured output signals and the desired output values (Patton, Frank, and Clark [1989]). Most of these fault detection techniques are proposed for open-loop systems. However, fault detection in closed-loop systems can be quite different with that in open-loop systems (Chowdhury and Chen [2007]). It is generally more difficult for fault detection and estimation, especially for the detection of incipient faults in presence of system disturbances.

As defined in the reference Demetriou and Polycarpou [1998]: incipient faults, represented by drift-type changes in system dynamics, are usually modeled as a drift in system parameters. Due to the small amplitudes and obscure early-stage symptoms of incipient faults, the conventional observer-based fault detection methods are rarely used for incipient faults in closed-loop systems (Chen and Chowdhury [2010]). The main difficulty in dealing with incipient faults in closed-loop systems is the compensating effect of feedback control strategy, which tends to diminish the effect of incipient faults on the tracking performance (Demetriou and Polycarpou [1998]). With the development of the adaptive and fault-tolerant control systems, closed-loop system can now be designed to well maintain the tracking performance despite the occurrence of incipient faults (Chowdhury [2006]). It should be pointed out that although the tracking performance could be maintained in those well-controlled systems, faults will increase the stress of actuators and bring high operating costs to the physical components (Chen and Yeh [2011]).

In order to detect the incipient faults in closed-loop systems accurately, more information is required. According to Xu and Jiang [2000], the best place to collect residuals for fault detection in closed-loop systems is the controller's output. Coincided with this viewpoint, total measurable fault information residual (ToMFIR) was then developed in the references (Chowdhury [2006]), where fault information in closed-loop system is divided into two parts: information collected at the plant outputs and information collected at the controller outputs. Output residual indicates the fault information that is uncompensated by the controller, while the compensated fault information lies in the controller residual (Chen and Yeh [2011]).

Because ToMFIR contains both controller and output residuals, the ToMFIR-based fault detection approaches are sensitive to incipient faults. The originally proposed ToMFIR-based fault detection approach and its followings are only suitable for linear and time-invariant systems, which limits their applications. This paper extends the ToMFIR-based fault detection approaches to a class of closed-loop nonlinear systems under the consideration of system disturbances. The main contributions are summarized as: (1) This paper takes into consideration of system disturbances and gives a more general form of ToMFIR-based fault detection framework; (2) The ToMFIR-based

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fault detection technique is extended for nonlinear closed-loop system; (3) Compared with Chowdhury [2006], the restriction on the fault type is removed; (4) A fault estimation method is developed for incipient actuator faults.

The organization of this paper is as follows. In section 2, a class of nonlinear system has been put under Takagi-Sugeno (T-S) form. The main technical results in this paper are given in section 3. In section 4, simulation results on a near space hypersonic vehicle (NSHV) are presented to demonstrate the effectiveness of the proposed approach. Finally, conclusion has been drawn in section 5.

2. SYSTEM DESCRIPTION

2.1 T-S Fuzzy Modeling for Nominal System

The following affine nonlinear system is considered:

$$\begin{cases} \dot{x} = f(x) + \sum_{i=1}^{m} g_i(x)u_i \\ y = h(x) \end{cases} \tag{1}$$

where $x \in R^n$ denotes the state vector, $u_i \in R^m$ denotes the control input vector, and $y \in R^n$ is the output vector. A fuzzy linear dynamic model has been proposed by Takagi and Sugeno to represent the local linear input and output relationships of a nonlinear system. The fuzzy linear model is described by fuzzy IF-THEN rules and can be used to deal with the fuzzy control problem. The nominal local linear model (represented by G_{0i}) has the form as Eq.(2) with its corresponding nominal input $u_0(t)$ and nominal output $y_0(t)$, where each implication is expressed by a linear state-space model. The i^{th} rule of this T-S fuzzy model is of the following form:

Plant Rule i : if $z_1(t)$ is M_{i1}, $z_2(t)$ is M_{i2}, ..., and $z_q(t)$ is M_{iq}, then

$$G_{0i}: \begin{cases} \dot{x}_0(t) = A^i x_0(t) + B^i u_0(t) \\ y_0(t) = C^i x_0(t) \end{cases} \tag{2}$$

where $i = 1, ..., N$, N is the number of IF-THEN rules, $z(t) = [z_1(t), ..., z_q(t)]^T$ are premise variables that are supposed to be known, $M_{ij}(j = 1, ..., q)$ represents the membership function of the premise variable z_j in rule i, $x_0(t) \in R^n$, $u_0(t) \in R^m$. $A^i \in R^{n\times n}$ and $B^i \in R^{n\times m}$ represent the local linear system models at the i^{th} operating point determined by the fuzzy rules.

The global fuzzy system is inferred as follows:

$$\begin{cases} \dot{x}_0(t) = \sum_{i=1}^{N} h_i(z(t))(A^i x_0(t) + B^i u_0(t)) \\ y_0(t) = \sum_{i=1}^{N} h_i(z(t)) C^i x_0(t) \end{cases} \tag{3}$$

where $h_i(z(t))$ is defined as:

$$h_i(z(t)) = \frac{\prod_{j=1}^{n} M_{ij}[z_j(t)]}{\sum_{i=1}^{N} \prod_{j=1}^{n} M_{ij}[z_j(t)]}, (i = 1, ..., N) \tag{4}$$

which represents the weight of each local linear model. $h_i(z(t))$ satisfies: $\sum_{i=1}^{N} h_i(z(t)) = 1$, $0 \le h_i(z(t)) \le 1$, for all t. In the following content, h_i denotes $h_i(z(t))$ for short. Assuming all state variables are measurable or at least observable, the output variables are the same as the state variables in this study, thus $C = C^i = I_n$, where n equals to the number of state variables. Considering the possible instability problem in the nonlinear systems in practice, the following nominal state feedback controller can be designed to stabilize the system.

Control Rule i : if $z_1(t)$ is M_{i1}, $z_2(t)$ is M_{i2}, ..., and $z_q(t)$ is M_{iq}, then

$$u_{0i}(t) = K_{ci} x_0(t) \tag{5}$$

where K_{ci} is the controller gain matrix to each operating point. The global fuzzy controller is given as follow:

$$u_0(t) = \sum_{i=1}^{N} h_i(K_{ci} x_0(t)) \tag{6}$$

The controller gain matrix K_{ci} is determined by solving the following linear matrix inequality (LMI):

$$P(A_i + B_i K_i) + (A_i + B_i K_i)^T P < -Q_i \tag{7}$$

where $P = P^T > 0$ and $Q_i > 0$ are the matrices with appropriate dimensions.

2.2 T-S Fuzzy Modeling for Real System With Actuator Faults

Without loss of generality, we assume the fault is the loss of actuator effectiveness. The real local linear model (represented by G_i) has the following form:

Faulty Plant Rule i : if $z_1(t)$ is M_{i1}, $z_2(t)$ is M_{i2}, ..., and $z_q(t)$ is M_{iq}, then

$$G_i: \begin{cases} \dot{x}(t) = A^i x(t) + B^i u^f(t) + Ed(t) \\ y(t) = C^i x(t) \end{cases} \tag{8}$$

where $y(t)$ denotes the output from the real local linear model, and $u(t)$ is the real control input, then the real global fuzzy model is described as following:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{N} h_i(A^i x(t) + B^i u^f(t)) + Ed(t) \\ y(t) = Cx(t) \end{cases} \tag{9}$$

where $u^f(t)$ is the faulty control input vector; $u^f(t) = [u_1^f(t), \cdots, u_m^f(t)]^T = F(t)u(t)$; $F(t)$ is a diagonal matrix function, $F(t) = diag\{\rho_1(t), \rho_2(t), \cdots, \rho_m(t)\}$, where $\rho_s(t)\ (1 \le s \le m)$ represents the remainder effectiveness of each actuator after fault occurs; m is the number of actuators; $\rho_s = 0$, $0 < \rho_s < 1$, $\rho_s = 1$ represents complete loss of control action, partial loss of control action and fault-free case respectively; $d(t)$ is a bounded external disturbance vector; E is the disturbance distribution matrix.

3. MAIN RESULTS

3.1 The detection mechanism of ToMFIR-based Approach

As described in section 2, the nominal local linear model (Eq.(2)) can be represented by $y_0(t) = G_{0i}u_0(t)$, while the real local linear model (Eq.(8) in presence of disturbance and actuator fault) can be represented by $y(t) = G_i u(t)$. Further, let $y^*(t) = G_{0i}u(t)$, where $y^*(t)$ is the output of the nominal system driven by actual real-time input $u(t)$.

Definition 1: The output residual $r_y(t)$, which describes the difference between the output of the real model and the nominal model, is defined as:

$$r_y(t) = y(t) - y_0(t) = G_i u(t) - G_{0i} u_0(t) \tag{10}$$

Definition 2: The controller residual $r_u(t)$ which represents the controller input adjustment is denoted as:

$$r_u(t) = u(t) - u_0(t) \tag{11}$$

where $u(t)$ should satisfy the stability requirement even in the fault case, *i.e.*, $u(t) = F^{-1}(t) \cdot u_0(t)$.

Definition 3: Observer residual is $r_{ob}(t) = \hat{y}(t) - y(t)$, when an observer is used to estimate the unmeasurable states.

Definition 4: The total measurable fault information residual, denoted by $ToMFIR_i$ is defined as the measured difference between the output of the real system and nominal system. The $ToMFIR_i$ is formed as:

ToMFIR Rule i : if $z_1(t)$ is M_{i1}, $z_2(t)$ is M_{i2}, ..., and $z_q(t)$ is M_{iq}, then

$$\begin{aligned} &ToMFIR_i(t) \\ &= y(t) - y^*(t) = G_i u(t) - G_{0i} u(t) \\ &= (G_i u(t) - G_{0i} u_0(t)) - (G_{0i} u(t) - G_{0i} u_0(t)) \\ &= r_y(t) - G_{0i} r_u(t) \end{aligned} \tag{12}$$

The global fuzzy total measurable fault information residual is inferred as follow:

$$ToMFIR(t) = \sum_{i=1}^{N} h_i \cdot ToMFIR_i(t) \tag{13}$$

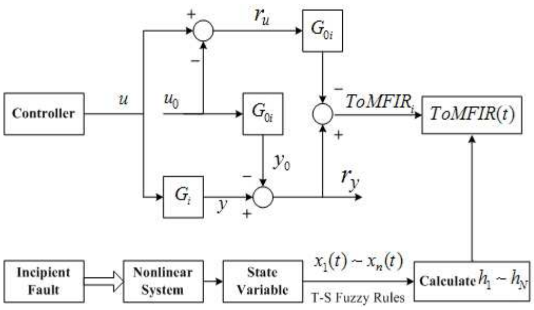

Fig. 1. The flow chart of designing global fuzzy ToMFIR

Remark 3.1.1: Fault detection can be performed by the following mechanism (λ is the detection threshold):

$$\|ToMFIR(t)\| \leq \lambda, no\ fault\ occurred \tag{14}$$

$$\|ToMFIR(t)\| > \lambda, fault\ has\ occurred \tag{15}$$

Remark 3.1.2: If a fault is so severe that the controller can't compensate it completely, such a fault can be detected by the conventional output residual based or observer residual based fault detection approaches by checking the condition $\|r_y(t)\| > \lambda$ or $\|r_{ob}(t)\| > \lambda$. If an incipient fault occurs, the fault may be compensated by the state feedback controller in the closed-loop system, fault indicators in the conventional approaches are likely within the threshold.

3.2 Convergence of ToMFIR

Theorem 1. For a real local linear model with actuator faults, the limiting value of $ToMFIR_i(t)$ is solely determined by the limiting value of the disturbance function and the system parameters (A^i, C, E), *i.e.*,

$$\lim_{t\to\infty} ToMFIR_i(t) = -C(A^i)^{-1} E \lim_{t\to\infty} d(t) \tag{16}$$

Proof. Let $r_x(t) = x(t) - x_0(t)$, then

$$\begin{cases} \dot{r}_x(t) = A^i r_x(t) + B^i r_u(t) + Ed(t) \\ r_y(t) = C r_x(t) \end{cases} \tag{17}$$

$$\begin{aligned} r_x(t) = e^{A^i(t-t^*)} r_x(t^*) + \int_{t^*}^{t} e^{A^i(t-\tau)} B^i r_u(\tau) d\tau \\ + \int_{t^*}^{t} e^{A^i(t-\tau)} E d(\tau) d\tau \end{aligned} \tag{18}$$

t^* represents the moment that fault occurs, so $r_x(t^*) = 0$ because the system is healthy before t^*.

$$\therefore r_x(t) = \int_{t^*}^{t} e^{A^i(t-\tau)} B^i r_u(\tau) d\tau + \int_{t^*}^{t} e^{A^i(t-\tau)} E d(\tau) d\tau \tag{19}$$

$$\lim_{t\to\infty} r_x(t) = -(A^i)^{-1} B^i \lim_{t\to\infty} r_u(t) - (A^i)^{-1} E \lim_{t\to\infty} d(t) \tag{20}$$

$$\lim_{t\to\infty} r_y(t) = -C(A^i)^{-1} B^i \lim_{t\to\infty} r_u(t) - C(A^i)^{-1} E \lim_{t\to\infty} d(t) \tag{21}$$

According to *Definition 4*,

$$\lim_{t\to\infty} ToMFIR_i(t) = \lim_{t\to\infty} r_y(t) - \lim_{t\to\infty} G_{0i} r_u(t) \tag{22}$$

such that

$$\begin{aligned} &\lim_{t\to\infty} ToMFIR_i(t) \\ &= \lim_{t\to\infty} r_y(t) + C(A^i)^{-1} B^i \lim_{t\to\infty} r_u(t) \\ &= -C(A^i)^{-1} B^i \lim_{t\to\infty} r_u(t) - C(A^i)^{-1} E \lim_{t\to\infty} d(t) \\ &+ C(A^i)^{-1} B^i \lim_{t\to\infty} r_u(t) \\ &= -C(A^i)^{-1} E \lim_{t\to\infty} d(t) \end{aligned} \tag{23}$$

Theorem 2. The disturbance function $d(t)$ is considered as a bounded external vector, so the $ToMFIR_i(t)$ is a bounded function. When $d(t)$ is small enough, the global fuzzy total measurable fault information residual $ToMFIR(t)$ can be used as a fault indicator.

Proof. $\because \sum_{i=1}^{N} h_i(z(t)) = 1$, $0 \leq h_i(z(t)) \leq 1$, then

$$\begin{aligned} \|ToMFIR(t)\| &= \left\| \sum_{i=1}^{N} h_i(z(t)) \cdot ToMFIR_i(t) \right\| \\ &\leq \sum_{i=1}^{N} 1 \cdot \|ToMFIR_i(t)\| = \sum_{i=1}^{N} \|ToMFIR_i(t)\| \end{aligned}$$

Remark 3.2.1: The originally proposed ToMFIR-based fault detection approach is effective only when the fault can converge to a constant value at steady state (Chowdhury [2006]). In this paper, this restriction is removed.

Remark 3.2.2: In Chowdhury [2006], the approximation $\widetilde{ToMFIR}_i(t) = r_y(t) + C(A^i)^{-1} B^i r_u(t)$ has been proved that it can converge to the true value of $ToMFIR_i(t)$. Thus, $\widetilde{ToMFIR}(t) = \sum_{i=1}^{N} h_i(r_y(t) + C(A^i)^{-1} B^i r_u(t))$ can be used as an effective fault indicator.

3.3 ToMFIR-based fault estimation

In order to estimate the incipient fault, a fuzzy state-space observer for the system Eq.(9) is described as follows:

Observer Rule i : if $z_1(t)$ is M_{i1} and $z_2(t)$ is M_{i2}, ..., and $z_q(t)$ is M_{iq}, then

$$\begin{cases} \dot{\hat{x}}(t) = A^i\hat{x}(t) + B^i\hat{F}u(t) + Ed(t) - L^i(\hat{y}(t) - y(t)) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \tag{24}$$

where L^i is the observer gain for the i^{th} observer rule. The global fuzzy system is inferred as follows:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{N} h_i \left[A^i\hat{x}(t) + B^i\hat{F}u(t) - L^i(\hat{y}(t) - y(t))\right] \\ \qquad + Ed(t) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \tag{25}$$

According to Chowdhury and Chen [2007], if the observer residual in a LTI system is pre-multiplied by a factor $M_i = C(A^i)^{-1}L^i - I$, with an identity matrix I, then the resulting function converges to the $ToMFIR_i(t)$ in a limiting sense, *i.e.*, $\lim_{t\to\infty} M_i r_{ob}(t) = \lim_{t\to\infty} ToMFIR_i(t)$, where $r_{ob}(t) = \hat{y}(t) - y(t)$. According to *Remark 3.2.2*, one can obtain that $M_i r_{ob}(t) = \widetilde{ToMFIR}_i(t)$.

The following ToMFIR-observer is constructed:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{N} h_i \left[A^i\hat{x}(t) + B^i\hat{F}u(t) - L^iM_i(\hat{y}(t) - y(t))\right] \\ \qquad + Ed(t) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \tag{26}$$

where $\hat{x}(t)$ is the observer state vector and $\hat{F}(t)$ is an estimate of $F(t)$. All diagonal elements in $\hat{F}(t)$ are set to 1 (represents fault-free case) until a fault is detected.

Denote: $e_x(t) = \hat{x}(t) - x(t)$, $e_f(t) = \hat{F}(t) - F(t)$, $e_y(t) = \hat{y}(t) - y(t) = Ce_x(t)$. An adaptive fault estimation algorithm is constructed as $d\hat{F}(t)/dt = -\Gamma \cdot \sum_{i=1}^{N} h_i \widetilde{ToMFIR}_i(t)$, then the error dynamic system is obtained as:

$$\begin{cases} \dot{e}_x(t) = \sum_{i=1}^{N} h_i \left\{ \left[A^i - L^iM_iC\right] e_x(t) + B^i e_f(t)u(t) \right\} \\ \dot{e}_f(t) = \sum_{i=1}^{N} h_i \left[-\Gamma \cdot M_iCe_x(t) - \dot{F}(t)\right] \end{cases} \tag{27}$$

Further, the global augmented system can be described as:

$$\dot{e}_{x|f}(t) = \sum_{i=1}^{N} h_i \left[(A^{i*} - L^{i*}C^*)e_{x|f}(t) + \varepsilon F^{i*}(t)\right] \tag{28}$$

where

$$e_{x|f}(t) = \begin{bmatrix} e_x(t) \\ e_f(t) \end{bmatrix}, A^{i*} = \begin{bmatrix} A^i & 0 \\ 0 & 0 \end{bmatrix}, \varepsilon = \begin{bmatrix} I & 0 \\ 0 & -1 \end{bmatrix},$$

$$L^{i*} = \begin{bmatrix} L^iM_i \\ \Gamma \cdot M_i \end{bmatrix}, C^* = [C\ 0], F^{i*} = \begin{bmatrix} B^ie_f(t)u(t) \\ \dot{F}(t) \end{bmatrix}$$

According to the Bounded Real Lemma, for a constant $\gamma > 0$, if there exists a symmetric matrix $P > 0$ and a matrix Y satisfying the following LMI:

$$\begin{bmatrix} PA^{i*} + (A^{i*})^T P - YC^* - (C^*)^T Y^T & P\varepsilon & I \\ * & -\gamma I & 0 \\ * & * & -\gamma I \end{bmatrix} < 0 \tag{29}$$

then the augmented observer can guarantee the convergence of state estimation error and fault estimation error. The proof can be referred to Jiang and Chowdhury [2005].

4. CASE STUDY

4.1 NSHV Dynamic Model

The dynamic model of NSHV was represented by a set of differential equations. The states are velocity V, flight-path angle γ, altitude h, angle of attack α, and pitch rate q (Shaughnessy and Pinchney [1990]).

$$\begin{cases} \dot{V} = (T\cos\alpha - D)/m \ - g\sin\gamma \\ \dot{\gamma} = (L + T\sin\alpha)/(mV) \ - (g\cos\gamma)/V \\ \dot{h} = V\sin\gamma \\ \dot{\alpha} = q - \dot{\gamma} \\ \dot{q} = M_{yy}/I_{yy} \end{cases} \tag{30}$$

The control input vector is $u(t) = [\delta_e, \delta_T]^T$, where δ_e is the elevator deflection, and δ_T is the throttle setting. The system output vector is $y = [V, \gamma, h, \alpha, q]^T \in R^5$. Considering the restrictive relationship between $V, \gamma, h, \alpha, and\ q$, angle of pitch θ, pitch rate q and velocity V are reselected as the new fuzzy variables (Xu and Jiang [2011]). The universes of discourse of each fuzzy variable is set as $\theta \in [-0.4, 0.4]rad$, $q \in [-0.4, 0.4]rad/s$, $V \in [1500, 4500]m/s$. The membership functions corresponding to each variables were given in Jiang, Gao, and Shi [2010]. For Rule i,

$$\begin{cases} M_{i1} = \exp[-(\theta/0.4)^2] \\ M_{i2} = 1/\{1 + \exp[(q^2 - 2000)/0.05]\} \\ M_{i3} = \exp[-(V/1000 \ - 0.15)] \end{cases} \tag{31}$$

where M_{i1}, M_{i2}, M_{i3} represents the membership function of $\theta, q, andV$ respectively. Choose 8 operating points and set $[\theta, q, V] = [-0.4, 0.4, 1500]$, $[0.4, 0.4, 1500]$, $[-0.4, -0.4, 1500]$, $[0.4, -0.4, 1500]$, $[-0.4, 0.4, 4500]$, $[0.4, 0.4, 4500]$, $[-0.4, -0.4, 4500]$, $[0.4, -0.4, 4500]$.

Then the real model with actuator fault at the given operating point can be described as:

$$\begin{cases} \dot{x}(t) = Ax(t) + BFu(t) + Ed(t) \\ y(t) = Cx(t) \end{cases}$$

where

$$A = \begin{bmatrix} -0.00078 & -31.4972 & 2*10^{(-9)} & -9.01 & 0 \\ 4*10^{(-6)} & 8*10^{(-6)} & 8*10^{(-10)} & 0.015 & 0 \\ 0.00072 & 4195.95 & 0 & 0 & 0 \\ -3*10^{(-6)} & -8*10^{(-6)} & -8*10^{(-10)} & -0.013 & 1 \\ 0.00044 & 0 & 0 & -6.01 & -235 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 2.5 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0.15 & 0 \end{bmatrix}, E = [-1\ 0\ 0\ 0\ 0]^T, d(t) = 0.002\sin(3\pi t).$$

In those literatures (Xu and Jiang [2011]; Jiang, Gao, and Shi [2010]) concerning with fault detection and isolation (FDI) or fault-tolerant control (FTC) problems in NSHV, the possible type of actuator faults have been discussed. NSHV has two actuators, where one is for changing the elevator deflection, the other is for throttle setting. In practice, the actuator for throttle setting is more reliable than the actuator for elevator deflection. So the faults are assumed to occur in the actuator for elevator deflection in this paper. The simulated actuator faults include:

Case 1 (drift fault):

$$\rho_1(t) = \begin{cases} 1, & 0 < t < 10 \\ \sigma_1 + \sigma_2 \cdot e^{-0.4(t-10)}, & 10 < t < 30 \end{cases}$$
$$\rho_2(t) = 1$$

where $(\sigma_1, \sigma_2) = (0.99, 0.01), (0.3, 0.7)$ represents an incipient fault (loss of effectiveness of 1%) and a serious slow drift fault (loss of effectiveness of 70%) respectively.

Case 2 (bias fault):

$$\rho_1(t) = \begin{cases} 1, & 0 < t < 10 \\ \sigma_1 + \sigma_2 \cdot cos(0.2\pi \cdot (t+10)), & 10 < t < 30 \end{cases}$$
$$\rho_2(t) = 1$$

where $(\sigma_1, \sigma_2) = (0.995, 0.005), (0.65, 0.35)$ represents a small bias fault (loss of effectiveness of 1%), a serious bias fault (loss of effectiveness of 70%) that doesn't converge to a constant value respectively.

4.2 Simulation Results

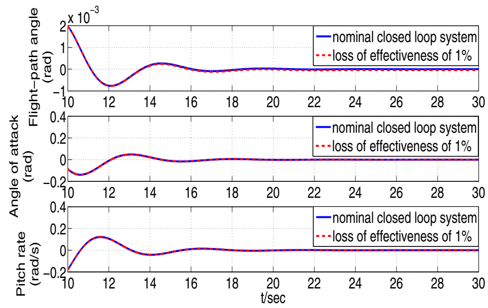

Fig. 2. Output Responses for case 1 (1% loss of effectiveness)

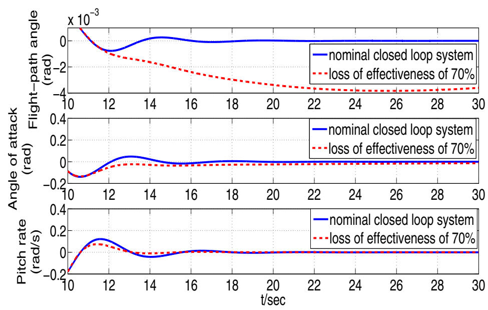

Fig. 3. Output Responses for case 1 (70% loss of effectiveness)

Remark 4.1: Fig.2 and Fig.3 show the output responses of the nominal model and the real model with an incipient actuator fault and a serious slow drift fault, respectively. From Fig.2, it can be seen that 1% loss of actuator effectiveness has nearly no influence on the output responses. Thus, this type of fault is defined as an incipient fault

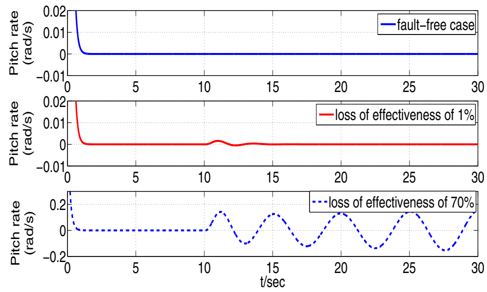

Fig. 4. Output residuals using an observer-based fault detection approach for case 1

in this paper. Not surprisingly, the output residual based approach has difficult in detecting this incipient fault, as shown in Fig.4.

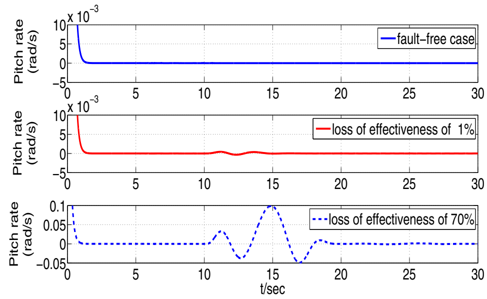

Fig. 5. Output residuals using an observer-based fault detection approach for case 2

Remark 4.2: Similar results have been obtained for case 2.

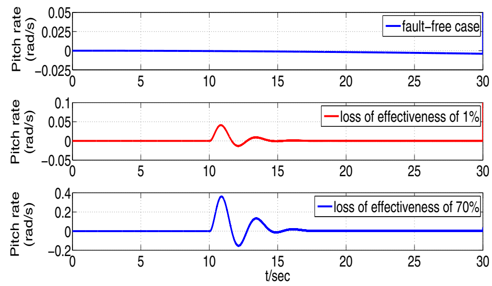

Fig. 6. ToMFIR based fault detection for case 1

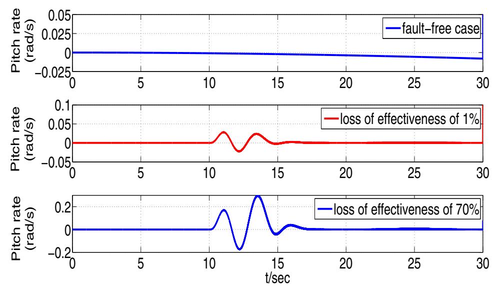

Fig. 7. ToMFIR based fault detection for case 2

Remark 4.3: Results using the proposed ToMFIR based approach are shown in Fig.6 and Fig.7. Compared with Fig.4 and Fig.5, the ToMFIR is more obvious than the

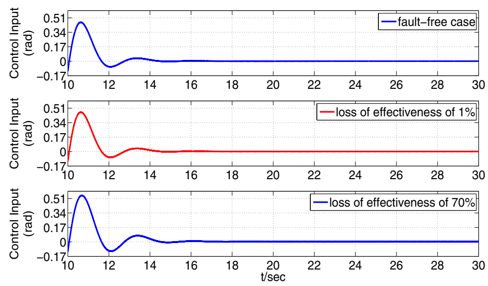

Fig. 8. Control Input Responses of (δ_T) for case 1

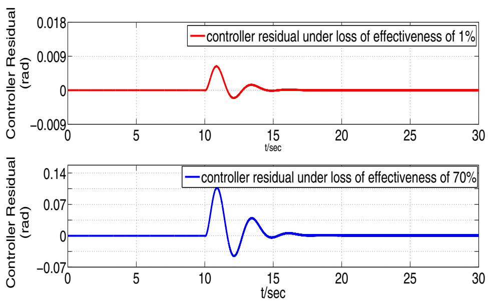

Fig. 9. Controller Residual of ($\triangle\ \delta_T$) for case 1

output residuals, which can guarantee the successful detection of incipient faults.

Remark 4.4: Fig.8 shows the control input responses δ_T for case 1. Fig.9 shows the controller residual ($\triangle\ \delta_T$). For incipient fault detection, although the controller residual (indicating the compensated fault information) is not large as shown Fig.9, it indeed contributes to the detection of the incipient faults.

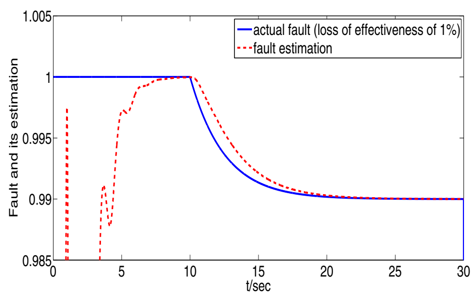

Fig. 10. Incipient fault estimation for case 1

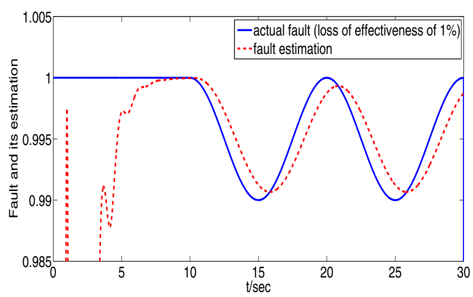

Fig. 11. Small bias fault estimation for case 2

Remark 4.5: ToMFIR-based fault estimation results are shown in Fig.10 and Fig.11. It can be seen that the proposed method can estimate the two types of faults accurately. The detection speed and estimation accuracy can be guaranteed at the same time. The restriction on the fault type (Chowdhury [2006]) is also removed.

5. CONCLUSION

This paper presents some new results for ToMFIR-based approach. The original approach was designed without any disturbances and the fault considered should converge to a constant value, which make the method ideal. Such restrictions have been removed in this paper and the ToMFIR-based method has been extended to a class of closed-loop nonlinear systems. The NSHV simulations have verified the effectiveness of the proposed fault detection and estimation strategy for incipient actuator fault.

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