Adaptive Observer-based Fast Fault Estimation

Ke Zhang, Bin Jiang*, and Vincent Cocquempot

Abstract: This paper studies the problem of fault estimation using adaptive fault diagnosis observer. A fast adaptive fault estimation (FAFE) approximator is proposed to improve the rapidity of fault estimation. Then based on linear matrix inequality (LMI) technique, a feasible algorithm is explored to solve the designed parameters. Furthermore, an extension to sensor fault case is investigated. Finally, simulation results are presented to illustrate the efficiency of the proposed FAFE methodology.

Keywords: Actuator and sensor fault, adaptive observer, fast fault estimation, fault diagnosis.

1. INTRODUCTION

Increased productivity requirements and stringent performance specifications lead to more demanding operating conditions of many modern engineering systems. Such conditions increase the possibility of system failures. Sensor, actuator or plant failures may drastically change the system behavior, resulting in degradation or even instability. In order to improve efficiency, the reliability can be achieved by fault tolerant control (FTC), which relies on early detection of faults, using fault detection and isolation (FDI) procedures. So FDI has become an attractive topic and received considerable attention during the past two decades. Fruitful results can be found in several excellent books [1-3], survey papers [4-6] and references therein.

In general, fault tolerance can be achieved in two ways: 1) passively, using feedback control laws that are robust with respect to possible system faults, or 2) actively, using a FDI module and accommodation technique. Active FTC is obtained by fault accommodation [7-9], which controls the faulty system, or by system reconfiguration, which controls the healthy part of the system. Therefore, in fault accommodation, FDI module must detect and isolate the faults, as well as estimate them. FDI is the first step in fault accommodation to monitor the system and determine the location of the fault. Then, fault estimation is utilized to on-line determine the magnitude of the fault. Finally, using the obtained fault information, an additive controller can be designed to compensate for the fault.

Some researchers pay more attention to adaptive fault diagnosis observer approach [8,10-14]. However, the main problems in the use of adaptive fault diagnosis observer are first to achieve the performance requirements of fault estimation, i.e., rapidity and accuracy, and second to fulfill the stringent constraint [15] and solve them to obtain the design parameters. Therefore, investigating an effective solution to overcome the above difficulties is necessary and motivates this paper.

The aim of this paper is to analyze model-based fault estimation schemes and develop a general framework for fast fault estimation based on adaptive observer. This extends earlier results of fault estimation using adaptive observer and provides a unified strategy for fast fault estimation in deterministic system. The main contributions of this paper are twofold. First, a FAFE algorithm only using the measurable input and output vector is proposed to enhance the rapidity of fault estimation, where the adaptive estimator composed of a proportional term and an integral one can guarantee both satisfactory dynamical and steady state performances. Second, design steps of the proposed strategy are given based on LMI technique, and this formulation gives an effective way to calculate the design parameters.

The rest of this paper is organized as follows. Section 2 gives system description for linear systems with actuator fault and the background on the conventional adaptive observer for fault estimation. In Section 3, the novel adaptive algorithm for actuator fault estimation is presented. An extension to sensor

Manuscript received September 15, 2007; accepted April 21, 2008. Recommended by Guest Editor Marcel Staroswiecki. This work was supported by National Natural Science Foundation of China (60574083), National “863” program of China (2006AA12A108) and Aeronautics Science Foundation of China (2007ZC52039).

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fault estimation is studied in Section 4. Simulation results of a vertical takeoff and landing (VTOL) aircraft system are given in Section 5, followed by some concluding remarks in Section 6.

2. PROBLEM STATEMENT

This section introduces the preliminaries and background for the work.

2.1. Systems description

Consider the following linear system with actuator fault

$$\dot{x}(t) = Ax(t) + Bu(t) + Ef_a(t), \quad (1)$$
$$y(t) = Cx(t), \quad (2)$$

where $x(t) \in R^n$ is the state vector, $u(t) \in R^m$ is the input vector, $y(t) \in R^p$ is the output vector and $f_a(t) \in R^r$ represents the actuator fault. A, B, E, and C are known constant real matrices of appropriate dimensions, the matrix E is of full column rank and the pair (A, C) is observable.

The failure $f_a(t) = \beta(t - t_f) f(t)$ can be thought of as an additive signal, and the function $\beta(t - t_f)$ is given by

$$\beta(t - t_f) = \begin{cases} 0, & t \le t_f \\ 1, & t > t_f, \end{cases} \quad (3)$$

where t_f is the time of fault occurring.

That is, $f_a(t)$ is zero prior to the failure time $(t \le t_f)$ and is $f(t)$ after the failure occurs $(t > t_f)$. It is assumed that the derivative of $f(t)$ with respect to time is norm bounded i.e., $\| \dot{f}(t) \| \le f_1$, where $0 \le f_1 < \infty$.

2.2. Conventional adaptive fault estimation design

The conventional adaptive fault diagnosis observer is firstly recalled and constructed as

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + E\hat{f}(t) - L(\hat{y}(t) - y(t)), \quad (4)$$
$$\hat{y}(t) = C\hat{x}(t), \quad (5)$$

where $\hat{x}(t) \in R^n$ is the observer state vector, $\hat{y}(t) \in R^p$ is the observer output vector and $\hat{f}(t) \in R^r$ is an estimate of actuator fault $f(t)$. Since it has been assumed that the pair (A, C) is observable, the observer gain matrix L can be selected such that $(A - LC)$ is a stable matrix.

Denote

$$e_x(t) = \hat{x}(t) - x(t), \quad e_y(t) = \hat{y}(t) - y(t),$$
$$e_f(t) = \hat{f}(t) - f(t), \quad (6)$$

then the error dynamics is described by

$$\dot{e}_x(t) = (A - LC)e_x(t) + Ee_f(t), \quad (7)$$
$$e_y(t) = Ce_x(t). \quad (8)$$

Generally speaking, constant fault, i.e., $\dot{f}(t) = 0$ is only considered based on the conventional algorithm, the derivative of $e_f(t)$ with respect to time can be written as

$$\dot{e}_f(t) = \dot{\hat{f}}(t). \quad (9)$$

Theorem 1: If there exist symmetric positive zefinite matrices $P, Q \in R^{n \times n}$, an observer gain observer $L \in R^{n \times p}$ and a matrix $F \in R^{r \times p}$ such that the following conditions hold

$$P(A - LC) + (A - LC)^T P = -Q, \quad (10)$$
$$E^T P = FC, \quad (11)$$

then the adaptive fault estimation algorithm

$$\dot{\hat{f}}(t) = -\Gamma F e_y(t) \quad (12)$$

can realize $\lim_{t \to \infty} e_x(t) = 0$ and $\lim_{t \to \infty} e_f(t) = 0$, where the symmetric positive definite matrix $\Gamma \in R^{r \times r}$ is the learning rate.

The proof of Theorem 1 can be referred to [8,10,11] and is omitted here.

Remark 1: Actuator fault estimate using the above method can be obtained

$$\hat{f}(t) = -\Gamma F \int_{t_f}^{t} e_y(\tau) d\tau. \quad (13)$$

In fact, this method is only pure integral term in essence. Although it guarantees that the constant fault estimation is unbiased, it fails to deal with time-varying fault. Therefore, we are motivated to improve the conventional adaptive algorithm so that time-varying fault can be considered using adaptive fault diagnosis observer.

3. FAST ACTUATOR FAULT ESTIMATION DESIGN

Before presenting the main results, two assumptions and two lemmas are given.

Assumption 1: rank $(CE) = r$.

Assumption 2: Invariant zeros of (A, E, C) lie in open left half plane (LHP).

Lemma 1 [11]**:** Given a scalar $\mu > 0$ and a symmetric positive definite matrix P, the following inequality holds:

$$2x^T y \le \frac{1}{\mu} x^T Px + \mu y^T P^{-1} y \quad x, y \in R^n. \tag{14}$$

Lemma 2 [16,17]**:** The conditions (10)-(11) hold if and only if Assumptions 1-2 hold.

Remark 2: Lemma 2 can be introduced to verify whether the adaptive fault diagnosis observer exists, whereas the existence conditions are not mentioned in [8,10,11].

As for time-varying faults, due to $\dot{f}(t) \ne 0$, the derivative of $e_f(t)$ with respect to time is

$$\dot{e}_f(t) = \dot{\hat{f}}(t) - \dot{f}(t). \tag{15}$$

Now we are ready to present our main results in this paper. A novel FAFE algorithm is proposed to improve performances of time-varying fault estimation. The stability of the error dynamics is guaranteed by the following theorem.

Theorem 2: Under Assumptions 1-2, given scalars $\sigma, \mu > 0$, if there exist symmetric positive definite matrices $P \in R^{n\times n}$, $G \in R^{r\times r}$, and matrices $Y \in R^{n\times p}$, $F \in R^{r\times p}$ such that (11) and the following condition hold

$$\begin{bmatrix} PA + A^T P - YC - C^T Y^T & -\frac{1}{\sigma}(A^T PE - C^T Y^T E) \\ * & -2\frac{1}{\sigma} E^T PE + \frac{1}{\sigma\mu} G \end{bmatrix} < 0, \tag{16}$$

where $Y = PL$ and $*$ denotes the symmetric elements in a symmetric matrix, then the FAFE algorithm

$$\dot{\hat{f}}(t) = -\Gamma F(\dot{e}_y(t) + \sigma e_y(t)) \tag{17}$$

can realize $e_x(t)$ and $e_f(t)$ uniformly ultimately bounded.

Proof: Consider the following Lyapunov function

$$V(t) = e_x^T(t) P e_x(t) + \frac{1}{\sigma} e_f^T(t) \Gamma^{-1} e_f(t). \tag{18}$$

From (7) and (17), its derivative with respect to time is

$$\begin{aligned} \dot{V}(t) &= \dot{e}_x^T(t) P e_x(t) + e_x^T(t) P \dot{e}_x(t) + 2\frac{1}{\sigma} e_f^T(t) \Gamma^{-1} \dot{e}_f(t) \\ &= e_x^T(t)(P(A - LC) + (A - LC)^T P) e_x(t) \\ &\quad + 2e_x^T(t) PE e_f(t) - 2\frac{1}{\sigma} e_f^T(t) F(\dot{e}_y(t) + \sigma e_y(t)) \\ &\quad -2\frac{1}{\sigma} e_f^T(t) \Gamma^{-1} \dot{f}(t). \end{aligned} \tag{19}$$

Using (11), it is easy to show that

$$\begin{aligned} &-2\frac{1}{\sigma} e_f^T(t) F(\dot{e}_y(t) + \sigma e_y(t)) \\ &= -2\frac{1}{\sigma} e_f^T(t) E^T P(\dot{e}_x(t) + \sigma e_x(t)). \end{aligned} \tag{20}$$

Substituting (7) and (20) into (19) yields

$$\begin{aligned} \dot{V}(t) &= e_x^T(t)(P(A - LC) + (A - LC)^T P) e_x(t) \\ &\quad - 2\frac{1}{\sigma} e_f^T(t) E^T P(A - LC) e_x(t) \\ &\quad - 2\frac{1}{\sigma} e_f^T(t) E^T PE e_f(t) - 2\frac{1}{\sigma} e_f^T(t) \Gamma^{-1} \dot{f}(t). \end{aligned} \tag{21}$$

From Lemma 1, we can obtain that

$$\begin{aligned} &-2\frac{1}{\sigma} e_f^T(t) \Gamma^{-1} \dot{f}(t) \\ &\le \frac{1}{\sigma\mu} e_f^T(t) G e_f(t) + \frac{\mu}{\sigma} \dot{f}^T(t) \Gamma^{-1} G^{-1} \Gamma^{-1} \dot{f}(t) \\ &\le \frac{1}{\sigma\mu} e_f^T(t) G e_f(t) + \frac{\mu}{\sigma} f_1^2 \lambda_{max}(\Gamma^{-1} G^{-1} \Gamma^{-1}). \end{aligned} \tag{22}$$

Substituting (22) into (21), one can further obtain that

$$\dot{V}(t) \le \zeta^T(t) \Xi \zeta(t) + \delta, \tag{23}$$

where

$$\Xi = \begin{bmatrix} P(A - LC) + (A - LC)^T P & -\frac{1}{\sigma}(A - LC)^T PE \\ * & -2\frac{1}{\sigma} E^T PE + \frac{1}{\sigma\mu} G \end{bmatrix},$$

$$\zeta(t) = \begin{bmatrix} e_x(t) \\ e_f(t) \end{bmatrix}, \quad \delta = \frac{\mu}{\sigma} f_1^2 \lambda_{max}(\Gamma^{-1} G^{-1} \Gamma^{-1}).$$

Because E is of full column, when $\Xi < 0$, one can obtain that $\dot{V}(t) < -\varepsilon \|\zeta(t)\|^2 + \delta$, where $\varepsilon = \lambda_{min}(-\Xi)$. It follows that $\dot{V}(t) < 0$ for $\varepsilon \|\zeta(t)\|^2 > \delta$, which means that $(e_x(t), e_f(t))$ converges to a small set according to Lyapunov stability theory. Therefore, estimation errors of the fault and the state are uniformly bounded. This is the end of proof. □

Remark 3: From (23), we can see that if $\dot{f}(t) = 0$, i.e., $f_1 = 0$, the proposed adaptive algorithm can achieve asymptotic estimate for constant fault, which indicates that the characteristic feature of conventional adaptive fault estimation algorithm is also reserved in the new one. Also, it is easy to show that the proposed FAFE algorithm combines proportional term with integral one.

$$\hat{f}(t) = -\Gamma F\left(e_y(t) + \sigma \int_{t_f}^{t} e_y(\tau)d\tau \right). \quad (24)$$

The introduction of the proportional term plays a major role to improve the rapidity of fault estimation.

Next, we will consider how to solve conditions in Theorem 2. It is easy to solve the inequality (16) by LMI toolbox, but the solving difficulty is added because of equation (11). Actually, it is a big problem to solve (11) and (16) simultaneously. This point is also not mentioned in [8,10,11]. Fortunately, we can transform (11) in Theorem 2 into the following optimization problem [16].

Minimize η subject to (16) and

$$\begin{bmatrix} \eta I & E^T P - FC \\ (E^T P - FC)^T & \eta I \end{bmatrix} > 0. \quad (25)$$

4. FAST SENSOR FAULT ESTIMATION DESIGN

All the results obtained in above sections are on actuator fault. The method is now extended to the sensor fault case. In this section, the system under consideration is

$$\dot{x}(t) = Ax(t) + Bu(t), \quad (26)$$

$$y(t) = Cx(t) + Df_s(t), \quad (27)$$

where $x(t) \in R^n$, $u(t) \in R^m$ and $y(t) \in R^p$ are the state, input and output vector respectively, $f_s(t) \in R^r$ represents the sensor fault. A, B, C and D are known constant real matrices of appropriate dimensions, the matrix D is of full column rank and the pair (A,C) is observable.

By constructing an augmented system [17], the obtained results can be extended to sensor fault estimation. Consider a new state $x_s(t) \in R^p$ that is a filtered version of $y(t)$

$$\dot{x}_s(t) = -A_s x_s(t) + A_s Cx(t) + A_s Df_s(t), \quad (28)$$

where $-A_s \in R^{p\times p}$ is a stable matrix.

Denote

$$\bar{x}(t) = \begin{bmatrix} x^T(t) & x_s^T(t) \end{bmatrix}^T, \quad (29)$$

then the augmented system can be expressed as

$$\dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{D}f_s(t), \quad (30)$$

$$\bar{y}(t) = \bar{C}\bar{x}(t), \quad (31)$$

where $\bar{A} \in R^{(n+p)\times(n+p)}$, $\bar{B} \in R^{(n+p)\times m}$, $\bar{D} \in R^{(n+p)\times r}$ and $\bar{C} \in R^{p\times(n+p)}$.

These matrices can be described as follows

$$\bar{A} = \begin{bmatrix} A & 0 \\ A_s C & -A_s \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} B \\ 0 \end{bmatrix},$$

$$\bar{D} = \begin{bmatrix} 0 \\ A_s D \end{bmatrix}, \quad \bar{C} = \begin{bmatrix} 0 & I_p \end{bmatrix}.$$

From the above augmented system, sensor fault may be treated as actuator fault. Moreover, in the augmented system, there is no more additive fault term in the output equation. Additionally, it can be easily proved that $(\bar{A},\bar{C})$ is observable if (A,C) is observable.

Assumption 3: rank $(\bar{C}\bar{D}) = r$.

Assumption 4: Invariant zeros of $(\bar{A},\bar{D},\bar{C})$ lie in open LHP.

Remark 4: Since we consider sensor fault as actuator fault, adaptive observer design and fault estimation strategy are similar to the above description. The following theorem is presented for sensor fault estimation, where the definition of matrix $\bar{L}$, variable $\bar{e}_y(t)$ can be referred in the previous section.

Theorem 3: Under Assumptions 3-4, given scalars $\sigma,\mu > 0$ if there exist symmetric positive definite matrices $\bar{P} \in R^{(n+p)\times(n+p)}$, $\bar{G} \in R^{r\times r}$, and matrices $\bar{Y} \in R^{(n+p)\times p}$, $\bar{F} \in R^{r\times p}$ such that the following conditions hold

$$\begin{bmatrix} \bar{P}\bar{A} + \bar{A}^T\bar{P} - \bar{Y}\bar{C} - \bar{C}^T\bar{Y}^T & -\frac{1}{\sigma}\left(\bar{A}^T\bar{P}\bar{D} - \bar{C}^T\bar{Y}^T\bar{D}\right) \\ * & -2\frac{1}{\sigma}\bar{D}^T\bar{P}\bar{D} + \frac{1}{\sigma\mu}\bar{G} \end{bmatrix} < 0, \quad (32)$$

$$\bar{D}^T\bar{P} = \bar{F}\bar{C}, \quad (33)$$

where $\bar{Y} = \bar{P}\bar{L}$ and $*$ denotes the symmetric elements in a symmetric matrix, then the FAFE algorithm

$$\dot{\hat{f}}(t) = -\Gamma\bar{F}\left(\dot{\bar{e}}_y(t) + \sigma\bar{e}_y(t)\right) \quad (34)$$

can realize $\bar{e}_x(t)$ and $\bar{e}_f(t)$ uniformly ultimately bounded.

The proof is similar to that of Theorem 2 and is omitted.

5. SIMULATION RESULTS AND ANALYSIS

A linearized dynamic model of a VTOL aircraft in the vertical plane is given in the state space formulation as [18]

$$\dot{x}(t) = Ax(t) + Bu(t) + Ef_a(t),$$
$$y(t) = Cx(t),$$

where $x(t) = [V_h, V_v, q, \theta]$, $u(t) = [\delta_c, \delta_l]$. The states and inputs are horizontal velocity V_h, vertical velocity V_v, pitch rate q, and pitch angle θ; collective pitch control δ_c and longitudinal cyclic pitch control δ_l. The model parameters are given as follows

$$A = \begin{bmatrix} -9.9477 & -0.7476 & 0.2632 & 5.0337 \\ 52.1659 & 2.7452 & 5.5532 & -24.4221 \\ 26.0922 & 2.6361 & -4.1975 & -19.2774 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 0.4422 & 0.1761 \\ 3.5446 & -7.5922 \\ 5.5200 & 4.4900 \\ 0 & 0 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

In this particular situation, an actuator fault will occur in the input channel and the actuator fault distribution matrix $E = B$. The pair (A, C) is observable, and it is easy to verify $\text{rank}(CE) = 2$ and (A, E, C) does not possess any invariant zeros and so the proposed method is applicable.

Actuator faults are only considered here while sensor faults are similar to actuator fault through augmenting system. Choosing $\sigma = 1$, $\mu = 1$ and solving (16) and (25), one can obtain that

$$\eta = 3.4916 \times 10^{-12},$$

$$P = \begin{bmatrix} 52.5807 & 5.3248 & 4.0848 & -36.6364 \\ 5.3248 & 0.9657 & 0.4648 & -4.8654 \\ 4.0848 & 0.4648 & 0.6257 & -2.5388 \\ -36.6346 & -4.8654 & -2.5388 & 33.6639 \end{bmatrix},$$

$$L = \begin{bmatrix} -5.5753 & -0.3164 & 6.9696 \\ 37.7198 & 3.6811 & 3.2809 \\ 34.1104 & 2.8060 & -29.5939 \\ 1.6496 & 0.4563 & 6.7482 \end{bmatrix},$$

$$F = \begin{bmatrix} 19.5775 & 3.2121 & -19.4315 \\ -12.8270 & -4.3072 & 19.0883 \end{bmatrix},$$

$$G = \begin{bmatrix} 8.5088 & -7.8022 \\ -7.8022 & 10.8916 \end{bmatrix}.$$

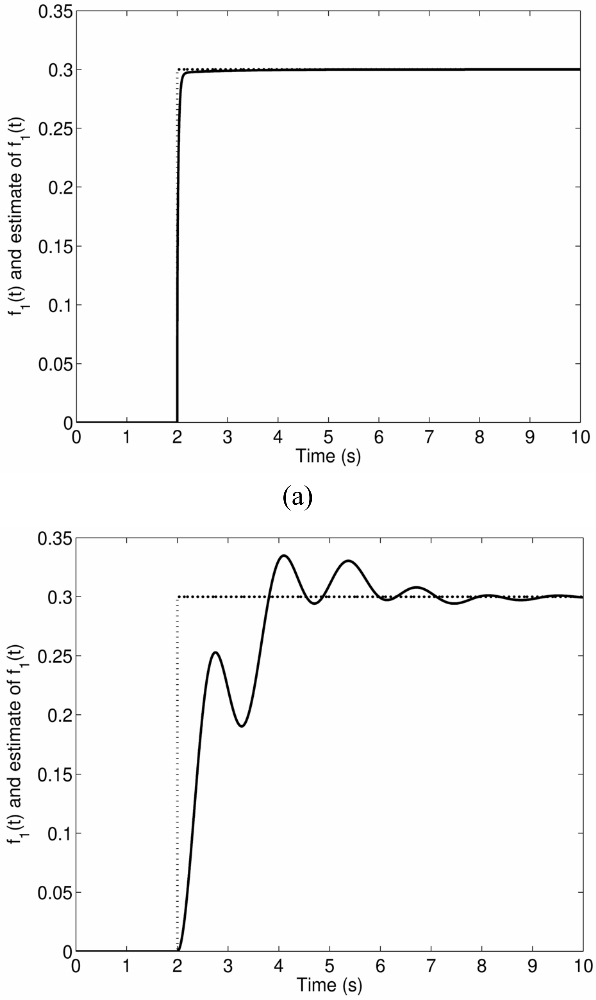


Fig. 1. Constant fault $f_1(t)$ (dotted line) and its estimate $\hat{f}_1(t)$ (solid line) using the FAFE algorithm and the conventional one.

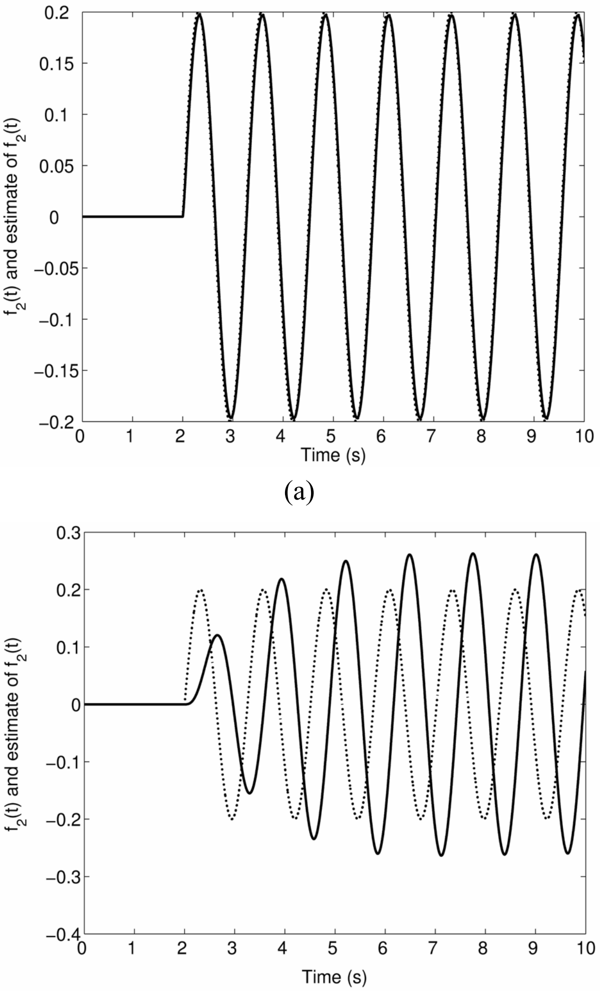
Taking the learning rate $\Gamma = diag(10,10)$ and sampling time $T = 0.01$ s, the system is subject to the reference input $u(t) = [1\ 1]^T$ and initial value $x(0) = [0\ 0\ 0\ 0]^T$. In order to show that proposed method is superior to the conventional one, we will compare them with the following simulations. There are two cases for the actuator fault $f(t) = [f_1(t)\ f_2(t)]^T$.

Assume that constant actuator fault is created as

$$f_1(t) = \begin{cases} 0 & 0 \le t \le 2 \\ 0.3 & 2 < t \le 10, \end{cases} \quad f_2(t) = 0.$$

The simulation results for constant fault estimation using the FAFE and conventional algorithm are shown in Fig. 1.

Then time-varying actuator fault is considered as



(a)

(b)

Fig. 2. Time-varying fault $f_2(t)$ (dotted line) and its estimate $\hat{f}_2(t)$ (solid line) using the FAFE algorithm and the conventional one.

$$f_2(t) = \begin{cases} 0 & 0 \le t \le 2 \\ 0.2\sin(5t-10) & 2 < t \le 10, \end{cases} \quad f_1(t) = 0.$$

Fig. 2 illustrates the simulation results for time-varying fault estimation using the above two mentioned methods.

From the above simulation results, it can be concluded that for constant fault, asymptotic convergence of fault estimation error can be both achieved using the two methods in accordance with the above theoretical analysis, but the proposed FAFE algorithm can improve the rapidity of fault estimation evidently. As for time-varying fault, the FAFE method can also enhance performances of time-varying fault estimation. Compared with the conventional adaptive approach for both constant and time-varying fault, the proposed FAFE method provides much better performances.

6. CONCLUSION

In this paper an adaptive observer technique for deterministic system has been developed for estimation of actuator and sensor fault. In particular it is obvious that the FAFE algorithm can improve performances of fault estimation, including constant and time-varying fault. The application of this scheme to a VTOL system shows that actuator fault can be estimated with satisfactory rapidity and accuracy.

Further research work includes two aspects. The first one is that fault accommodation strategy-based fault-tolerant controller will be designed to compensate for these faults using the FAFE algorithm, which can guarantee the stability and reliability of control systems. Since most of industrial systems are uncertain and nonlinear, extension of the proposed method to robust fault diagnosis for uncertain nonlinear systems is another interesting issue.

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