Observer-based Fault Diagnosis for a Class of Nonlinear Systems

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***Abstract*— The focus of this paper is the detection and diagnosis of parameter faults in nonlinear systems. The novelty of this contribution is that it handles the nonlinear fault distribution function. Since such a fault distribution function depends not only on the inputs and outputs of the system but also on unmeasured states, it causes additional complexity in fault estimation. The proposed diagnostic tool is based on the adaptive observer technique. Under the Lipschitz condition, a fault detection observer and adaptive diagnosis observer are proposed. Then, relaxation of the Lipschitz requirement is proposed and the necessary modification to the diagnostic tool is presented. Finally, the example of a one-wheel model with lumped friction is presented to illustrate the applicability of the proposed diagnosis method.**

I. INTRODUCTION

Fault detection and isolation (FDI) algorithms and their applications to a wide range of industrial processes have been the subject of intensive research over the past two decades. Fruitful results can be found in several survey papers [1], [2] and books [3], [4], [5]. In general, there are several kinds of schemes for model-based FDI: observer based, [6], [7], [8], parity space based, [9], [10], eigen-structure assignment based [11] and parameter-identification based [12]. In some cases, fault accommodation strategies are needed, i.e. the control algorithm must be adapted based on FDI to go on controlling the faulty system. In such cases, it is important to carry out fault diagnosis/identification in addition to detection. Recently, some results for fault diagnosis/identification have been obtained; for example, see [13], [14], [15], [16], [17] for techniques based on adaptive or robust observers, and see [18], [19] for methods using learning approach. In this paper, detection and diagnosis of parameter faults for nonlinear systems are investigated using adaptive observers. Compared with [18], [20] and our previous work presented in [16], the novelty of this contribution is that we consider difficult cases where the nonlinear fault distribution function depends not only on the inputs and outputs but also on unmeasured states. Furthermore, in order to expand the applicability of the proposed method, we propose a relaxation of the Lipschitz condition which is typically required (e.g., [21], [22], [16]) in FDI literature. This paper is organized as follows. Section 2 describes a class of nonlinear systems with parameter fault and introduces some preliminaries. Under Lipschitz condition, fault detection observer is proposed in section 3. An adaptive diagnostic rule is designed in section 4. Discussion on relaxation of Lipschitz requirement is presented in section 5. Results of applying our technique to a one-wheel model with lumped friction are presented in section 6, followed by some concluding remarks in section 7.

II. NONLINEAR DYNAMIC MODEL

Consider the following nonlinear system

$$\begin{aligned} \dot{x}(t) &= Ax(t) + g(u(t), y(t)) \\ &\quad + B\theta(t) f(u(t), y(t), x(t)) \qquad (1) \\ y(t) &= Cx(t) \qquad (2) \end{aligned}$$

where the state is $x \in R^n$, the input is $u \in \mathbf{R}^m$, and the output is $y \in \mathbf{R}^r$. The pair (A, C) is observable. The nonlinear term $g(u(t), y(t))$ depends on $u(t)$ and $y(t)$ which are directly available. The $f(u(t), y(t), x(t)) \in \mathbf{R}^r$ is a nonlinear vector function of $u(t), y(t)$ and $x(t)$. The $\theta(t) \in \mathbf{R}$ is a parameter which changes unexpectedly when a fault occurs. It is assumed that $\theta(t)$ is bounded, i.e., $\mid \theta(t) \mid \leq \theta_0$. In the fault-free case, we have $\theta(t) = \theta_H$, where θ_H is a known scalar (subscript H stands for healthy case).

III. DETECTION OBSERVER DESIGN

Clearly, the goal of the detection observer is to generate the fault indicators (residuals). The function of the detection observer can be replaced by other techniques, for example, using the plant model directly if the initial conditions are known. Prior to fault detection observer design, the following assumptions are made:

Assumption 1: There exists a known positive constant L_0 such that for any norm bounded $x_1(t), x_2(t) \in \mathbf{R}^n$, the following inequality holds:

$$\begin{aligned} &\|f(u(t), y(t), x_1(t)) - f(u(t), y(t), x_2(t))\| \\ &\leq \; L_0 \|x_1(t) - x_2(t)\| \qquad (3) \end{aligned}$$

Remark 1: Assumption 1 is the known Lipschitz condition, which is typically required in the literature on FDI for nonlinear systems, e.g., [21], [22], [16]. The removal of the Lipschitz condition for detection observer design will be discussed later in the paper.

Assumption 2: $C[sI-(A-KC)]^{-1}B$ is strictly positive real (SPR), where $K \in \mathbf{R}^{n\times r}$ is chosen such that $A-KC$ is stable.

Remark 2: The SPR requirement in the above assumption is equivalent to the following : For a given positive definite matrix $Q > 0 \in \mathbf{R}^{n\times n}$, there exists matrices $P = P^T > 0 \in \mathbf{R}^{n\times n}$ and a scalar R such that

$$(A-KC)^T P + P(A-KC) = -Q \quad (4)$$
$$PB = C^T R \quad (5)$$

To detect the fault, the following observer is constructed:

$$\begin{aligned}\dot{\hat{x}}(t) &= A\hat{x}(t) + g(u(t),y(t)) + B\theta_H f(u(t),y(t),\hat{x}(t)) \\ &\quad +K(y(t)-\hat{y}(t)) \quad (6)\\ \hat{y}(t) &= C\hat{x}(t) \quad (7)\end{aligned}$$

where $\hat{x}(t) \in \mathbf{R}^n$ is the state estimate. Since it has been assumed that the pair (A, C) is observable, the observer gain matrix K can be selected such that $(A-KC)$ is a stable matrix. Define

$$e_x(t) = x(t)-\hat{x}(t), \quad e_y(t) = y(t)-\hat{y}(t). \quad (8)$$

Then the observation error and output error equations are given by

$$\begin{aligned}\dot{e}_x(t) &= (A-KC)e_x(t) + B[\theta(t)f(u(t),y(t),x(t)) \\ &\quad -\theta_H f(u(t),y(t),\hat{x}(t))] \quad (9)\\ e_y(t) &= Ce_x(t) \quad (10)\end{aligned}$$

The convergence of the above observer is guaranteed by the following theorem:

Theorem 1: Consider the system described by (1), (2) and its observer described by (6), (7). Under Assumptions 1-2, the observer is asymptotically convergent when no faults occurs ($\theta(t) = \theta_H$) , i.e., $\lim_{t\to\infty} e_x(t) = 0$ and thus $\lim_{t\to\infty} e_y(t) = 0$.

Proof: Consider the following Lyapunov function

$$V(t) = e_x^T(t)Pe_x(t) \quad (11)$$

where P is given by (4) and (5), Q is chosen such that $\rho_1 \overset{\triangle}{=} \lambda_{min}(Q) - 2\|C\|\cdot \mid R \mid \theta_H L_0 > 0$.

Along the trajectory of the fault-free system (9), its derivative with respect to time is

$$\begin{aligned}\dot{V}(t) &= e_x^T(t)[P(A-KC) + (A-KC)^T P]e_x(t) \\ &\quad +2e_x^T(t)PB\theta_H[f(u(t),y(t),x(t)) \\ &\quad -f(u(t),y(t),\hat{x}(t))] \quad (12)\end{aligned}$$

From (3), (4), and (5), one can further obtain that

$$\begin{aligned}\dot{V}(t) &\le -e_x^T(t)Qe_x(t) \\ &\quad +2\|e_y\|\cdot \mid R \mid \theta_H L_0\|e_x\| \quad (13)\\ &\le -\rho_1\|e_x\|^2 \le 0\end{aligned}$$

Thus $\lim_{t\to\infty} e_x(t) = 0$ and $\lim_{t\to\infty} e_y(t) = 0$. This completes the proof.

The proposed method will be applicable under the assumption that the observer can converge during the no-fault period of the system operation. According to Theorem 1, after the convergence of the observer, the fault detection can be carried out as follows:

$$\left.\begin{aligned} e_y(t) = 0, &\quad \text{no fault occurred} \\ e_y(t) \neq 0, &\quad \text{fault has occurred.}\end{aligned}\right\} \quad (14)$$

The observer given by (6) and (7) is referred to as a detection observer for the system described by (1) and (2) under assumptions 1-2.

IV. Fault diagnostic observer design

To diagnose the fault after the alarm (14) has been generated, the following observer is constructed:

$$\begin{aligned}\dot{\hat{x}}(t) &= A\hat{x}(t) + g(u(t),y(t)) + B\hat{\theta}(t)f(u(t),y(t),\hat{x}(t)) \\ &\quad +K(y(t)-\hat{y}(t)) \quad (15)\\ \hat{y}(t) &= C\hat{x}(t) \quad (16)\end{aligned}$$

where $\hat{x}(t) \in R^n$ is the observer state vector and $\hat{\theta}(t)$ is an estimate of $\theta(t)$. The value of $\hat{\theta}(t)$ is set to θ_H until a fault is detected. It is assumed that after a fault occurs, $\theta(t) = \theta_f = constant \neq \theta_H, \mid \theta_f \mid \le \theta_0$.

Denote

$$e_x(t) = x(t)-\hat{x}(t),\ e_y(t) = y(t)-\hat{y}(t),\ e_\theta(t) = \theta_f-\hat{\theta}(t). \quad (17)$$

then it can be obtained that

$$\begin{aligned}\dot{e}_x(t) &= (A-KC)e_x(t) + B[\theta_f f(u(t),y(t),x(t)) \\ &\quad -\hat{\theta}(t)f(u(t),y(t),\hat{x}(t))] \quad (18)\\ e_y(t) &= Ce_x(t) \quad (19)\end{aligned}$$

As a result, the purpose of fault diagnosis is to find a diagnostic algorithm for $\hat{\theta}(t)$ such that

$$\lim_{t\to\infty} e_x(t) = 0, \quad \lim_{t\to\infty} e_\theta(t) = 0. \quad (20)$$

The following theorem produces a convergent adaptive diagnostic algorithm for estimating the faulty parameter θ_f.

Theorem 2: Under the Assumptions 1-2, the observer described by (15) and (16) and following diagnostic algorithm

$$\frac{d\hat{\theta}(t)}{dt} = \Gamma f^T(u(t),y(t),\hat{x}(t))Re_y(t) \quad (21)$$

can realize $\lim_{t\to\infty} e_x(t) = 0$ and a bounded $e_\theta(t) \in L^2$. Furthermore, $\lim_{t\to\infty} e_\theta(t) = 0$ under a persistent excitation, where R is given by (5), $\Gamma > 0$ is a weighting scalar.

Proof: Consider the following Lyapunov function

$$V(t) = e_x^T(t)Pe_x(t) + \Gamma^{-1}e_\theta^2(t) \quad (22)$$

From (18) and (21), its derivative with respect to time is

$$\begin{aligned}\dot{V}(t) &= e_x^T(t)[P(A-KC) + (A-KC)^T P]e_x(t) \\ &\quad -2e_\theta(t)f^T(u(t),y(t),\hat{x}(t))Re_y(t) \\ &\quad +2e_x^T(t)PB[\theta_f f(u(t),y(t),x(t)) \\ &\quad -\hat{\theta}(t)f(u(t),y(t),\hat{x}(t))] \quad (23)\end{aligned}$$

According to Assumptions 1-2, one can further obtain that

$$\begin{aligned}\dot{V}(t) \leq & -e_x^T(t)Qe_x(t) - 2e_\theta(t)f^T(u(t),y(t),\hat{x}(t))Re_y(t) \\ & +2e_x^T C^T R\{e_\theta f(u,y,\hat{x}) \\ & +\theta_f[f(u,y,x) - f(u,y,\hat{x})]\} \\ \leq & -\rho_2\|e_x\|^2 \leq 0 \end{aligned} \quad (24)$$

where $\rho_2 \stackrel{\triangle}{=} \lambda_{min}(Q) - 2\|C\| \cdot \mid R \mid \theta_0 L_0, \ \mid \theta_f \mid \leq \theta_0, \ Q > 0$ is chosen such that $\rho_2 > 0$.

Inequality (24) implies the stability of the origin $e_x = 0, e_\theta = 0$ and the uniform boundedness of e_x and e_θ with $e_x \in L_2$. On the other hand, from (18), $\dot{e}_x$ is uniformly bounded as well. According to Barbalat's Lemma (see [23]), one can get

$$\lim_{t\to\infty} e_x(t) = 0 \quad (25)$$

The persistent excitation condition means that there exist two positive constants σ and t_0 such that for all t the following inequality holds

$$\begin{aligned}&\int_t^{t+t_0} f^T(y(s),u(s),x(s))B^T B f^T(y(s),u(s),x(s)) \ ds \\ &\geq \ \ \sigma I \end{aligned} \quad (26)$$

Then from (18), (21), (25) and (26), one can conclude that $\lim_{t\to\infty} e_\theta(t) = 0$. This completes the proof.

Remark 3: The choice/design of K, Q, P and R is summarized as follows:

i) Since (A, C) is observable, the observer gain matrix K is selected such that $(A - KC)$ is stable and $C[sI - (A - KC)]^{-1}B$ is strictly positive real (SPR).

ii) In Eq. (4), $Q > 0$ is chosen such that the above defined $\rho_2 > 0$.

iii) The existence of solutions P and R to Eqs. (4)-(5) can be explained by Remark 2.

V. Relaxing the Lipschitz requirement

In the above sections, fault detection and diagnosis observers have been designed under the Lipschitz condition which does not always hold for practical systems. In this section, we replace the Lipschitz requirement by the following, weaker condition:

Assumption 1': There exists a positive function $q(\cdot)$ and a positive scalar q_0 such that the following inequality holds:

$$\|f(u(t),y(t),x(t))\| \leq q(\|x\|) \leq q_0 \quad (27)$$

The focus of this section is to design an adaptive diagnostic observer under Assumption 1' instead of Assumption 1. The detection observer can be designed similarly and is omitted.

To diagnose the fault after detection, the following observer is constructed:

$$\begin{aligned}\dot{\hat{x}}(t) = & A\hat{x}(t) + g(u(t),y(t)) \\ & +B\hat{\theta}(t)f(u(t),y(t),\hat{x}(t)) + K(y(t) - \hat{y}(t)) \\ & +Bsgn(R)[\theta_0(q_0 + q(\|x\|)) \\ & \times sgn(y(t) - \hat{y}(t))] \end{aligned} \quad (28)$$

$$\hat{y}(t) = C\hat{x}(t) \quad (29)$$

where $\hat{x}(t) \in R^n$ is the observer state vector and $\hat{\theta}(t)$ is an estimate of $\theta(t)$, which is obtained by the diagnostic algorithm (21).

Remark 4: From (28), it can be seen that the Lipschitz condition can be relaxed at the cost of an additional term in the diagnostic observer design.

Using the same notations of $e_x(t), e_y(t)$ and $e_\theta(t)$ as in section 4, then the observation error and output error equations can be described by

$$\begin{aligned}\dot{e}_x(t) = & (A - KC)e_x(t) \\ & +B[\theta_f f(u(t),y(t),x(t)) - \hat{\theta}(t)f(u(t),y(t),\hat{x}(t))] \\ & -Bsgn(R)[\theta_0(q_0 + q(\|x\|))sgn(y(t) - \hat{y}(t))] \end{aligned} \quad (30)$$

$$e_y(t) = Ce_x(t) \quad (31)$$

Theorem 3: Under the Assumptions 1' and Assumption 2, the observer described by (28) and (29) and the diagnostic algorithm described by (21) can realize $\lim_{t\to\infty} e_x(t) = 0$ and a bounded $e_\theta(t) \in L^2$. Furthermore, $\lim_{t\to\infty} e_\theta(t) = 0$ under persistent excitation conditions.

Proof: The proof of this theorem is similar to that of Theorem 2 and is omitted here.

Remark 5: This work is an extension of that in [14] to Lipschitz and bounded nonlinear fault distribution functions.

Remark 6: It is worth pointing out that a similar issue has been investigated by some researchers, for example, [7] based on high-gain observer, [8] using differential geometric theory, [19] via learning approach. The contribution of the results obtained in this paper is that it not only enables parameter fault detection, but also provides the estimation of the fault which is required for fault accommodation.

Remark 7: From Theorems 2-3, it can be seen that exact estimation of constant fault can be achieved by diagnostic algorithm (21). However, assumption of constant fault does not always hold for practical systems. If parameter faults are time varying, a similar method as in [16] can be used to guarantee convergence of fault estimation error to a residual set.

VI. Application example: a one-wheel model with lumped friction

To illustrate the effectiveness of the proposed technique in this paper, let us consider a one-wheel model with the lumped tire/road friction model as described in [24]:

$$m\dot{\upsilon} = F_n(\sigma_0 z + \sigma_1 \dot{z}) + F_n\sigma_2\upsilon_r \quad (32)$$

$$J\dot{\omega} = -rF_n(\sigma_0 z + \sigma_1 \dot{z}) - \sigma_\omega\omega + u_\tau \quad (33)$$

$$\dot{z} = \upsilon_r - \theta\frac{\sigma_0 \mid \upsilon_r \mid}{g(\upsilon_r)} z \quad (34)$$

where $g(\upsilon_r) = \mu_c + (\mu_s - \mu_c)e^{-|\upsilon_r/\upsilon_s|^{1/2}}$, σ_0 is the normalized rubber longitudinal lumped stiffness, σ_1 the normalized rubber longitudinal lumped damping, σ_2 the normalized viscous relative damping, σ_ω the viscous rotational friction, μ_c the normalized coulomb friction, μ_s the normalized static friction, $\mu_c \leq \mu_s \in [0,1]$, υ_s the Stribeck relative velocity, $v_r = (r\omega - v)$ the relative velocity, v the linear velocity, ω the angular velocity, F_n the normal force, z the internal friction state. θ denotes the parameter related to the unexpected changes in the road conditions, which can be interpreted as being the coefficient of road adhesion. In normal case, $\theta = 1$. It is assumed that only ω is measurable.

By introducing the following transformation of coordinates into the system described by (32)-(34):

$$\xi = rmv + J\omega \quad (35)$$

$$\eta = J\omega + rF_n\sigma_1 z \quad (36)$$

One can obtain

$$\dot{\xi} = -\frac{F_n\sigma_2}{m}\,\xi + u_\tau + (\frac{JF_n\sigma_2}{m} + r^2F_n\sigma_2 - \sigma_\omega)\omega \quad (37)$$

$$\dot{\eta} = -\frac{\sigma_0}{\sigma_1}\,\eta + (J\frac{\sigma_0}{\sigma_1} - \sigma\omega)\omega + u_\tau \quad (38)$$

$$\dot{z} = (r\omega - v) - \theta\sigma_0\frac{\mid r\omega - v\mid}{g(v_r)}\,z \quad (39)$$

$$y = \frac{1}{J}(\eta - rF_n\sigma_1 z) = \omega \quad (40)$$

By defining $x = \begin{bmatrix} \xi \\ \eta \\ z \end{bmatrix}$, $u = u_\tau,\ y = \omega$, one can rewrite the above system as state-space form

$$\begin{aligned}\dot{x} &= \begin{bmatrix} -\frac{F_n\sigma_2}{m} & 0 & 0 \\ 0 & -\frac{\sigma_0}{\sigma_1} & 0 \\ -\frac{1}{rm} & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \theta\,\frac{\sigma_0 \mid r\omega - v\mid}{g(v_r)}\,z + \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} u \\ &+ \begin{bmatrix} (\frac{JF_n\sigma_2}{m} + r^2F_n\sigma_2 - \sigma_\omega) \\ (J\frac{\sigma_0}{\sigma_1} - \sigma_\omega) \\ r \end{bmatrix} y \end{aligned} \quad (41)$$

$$y = \begin{bmatrix} 0 \\ 1/J \\ -rF_n\sigma_1/J \end{bmatrix}^T x \quad (42)$$

As in [24], the following values of parameters for the wheel are taken:

$$\sigma_0 = 40(1/m),\ \sigma_1 = 4.9487(s/m),\ \sigma_2 = 0.0018(s/m);$$

$$\mu_c = 0.5,\ \mu_s = 0.9,\ v_s = 12.5(m/s);$$

$$r = 0.25(m),\ m = 5(Kg);$$

$$J = 0.2344(Kgm^2),\ F_n = 14(Kgm^2/s^2).$$

Using the above numerical values of parameters, the system matrices in Eqs. (1) and (2) are:

$$A = \begin{bmatrix} -0.0050 & 0 & 0 \\ 0 & -8.0923 & 0 \\ -0.80 & 0 & 0 \end{bmatrix};$$

$$B = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}, \quad C = \begin{bmatrix} 0 \\ 4.2662 \\ 73.8927 \end{bmatrix}^T.$$

It is easy to see that $rank[C\ CA\ CA^2] = 3$, thus (A, C) is an observable pair.

$$\begin{aligned} f(u,y,x) &= \frac{\sigma_0 \mid r\omega - v\mid}{g(v_r)}\,z \\ &\le \frac{\sigma_0}{\mu_c}\mid r\omega - v\mid \cdot \mid z\mid \\ &\le \frac{\sigma_0}{\mu_c}(\mid ry\mid + \mid v\mid)\cdot\mid z\mid \\ &\le \frac{\sigma_0}{\mu_c}\left[(r + \frac{J}{rm})y_{max} + \frac{\mid\xi\mid}{rm}\right]\cdot\mid z\mid \\ &\triangleq q(\|x\|) \end{aligned}$$

and that

$$\begin{aligned} f(u,y,\hat{x}) &\le \frac{\sigma_0}{\mu_c}\left[(r + \frac{J}{rm})y_{max} + \frac{\mid\hat{\xi}\mid}{rm}\right]\cdot\mid\hat{z}\mid \\ &\triangleq q(\|\hat{x}\|) \end{aligned}$$

However, it can be checked that $f(u, y, x)$ in this example does not satisfy Lipschitz condition (i.e., a Lipschitz constant does not exist), thus those fault detection methods subjected to such a condition can not be used for this practical example.

The persistent excitation condition implies that the relative velocity $v_r = (r\omega - v)$ should not tend to zero in order for the estimated parameter to converge. This in turn implies that the internal friction state $z(t)$ will not asymptotically converge to zero.

In the simulation, by choosing

$$K = \begin{bmatrix} -0.1250 \\ -0.2308 \\ 0.0661 \end{bmatrix};$$

$$Q = \begin{bmatrix} 0.0548 & 0.2738 & 9.0206 \\ 0.2738 & 38.1191 & 29.4727 \\ 9.0206 & 29.4727 & 576.3141 \end{bmatrix};$$

One obtains

$$P = \begin{bmatrix} 5.4797 & -0.0305 & 0 \\ -0.0305 & 2.51 & 4.2662 \\ 0 & 4.2662 & 73.8927 \end{bmatrix}, \quad R = -1.$$

Assume that the parameter fault is created as follows:

$$\theta(t) = \begin{cases} 1; & t < 4 \text{ (sec)} \\ 2.5; & 4 \le t \le 10 \text{ (sec)} \end{cases}$$

Thus it is verified that all the assumptions are satisfied in this practical example. By taking the parameter $\Gamma = 100$ and the sampling period $T = 0.01$, the simulation results are shown in Fig. 1 and Fig. 2. It can be seen that the parameter fault is both detected and estimated quickly.

VII. Conclusions

In this paper, adaptive observer-based detection and diagnosis of parameter faults in a class of nonlinear systems with nonlinear fault distribution is proposed. Adaptive observer design for fault detection and diagnosis is presented, and it is shown that the Lipschitz condition can be relaxed at the cost of an additional term in the diagnostic observer design. A one-wheel model with lumped friction is used as the application example to verify the effectiveness of the approach.

VIII. ACKNOWLEDGMENTS

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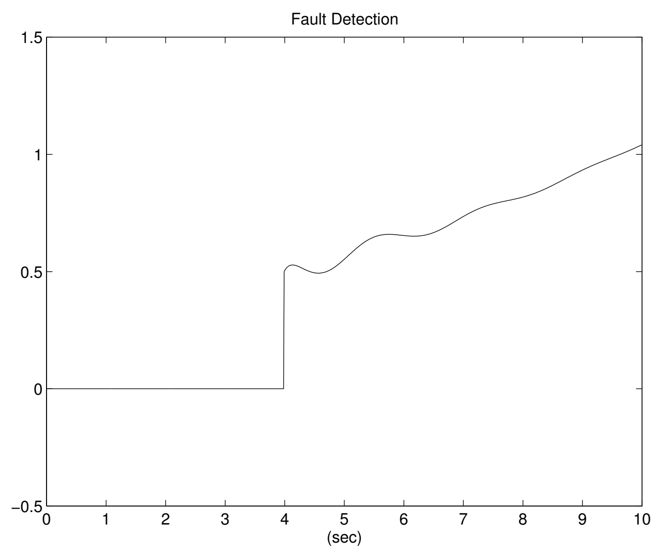

Fig. 1. Detection signal: $\| e_y(t) \|$.

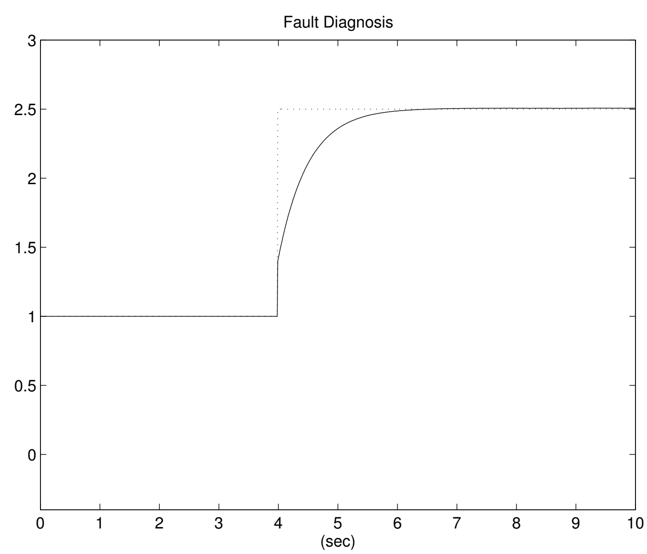

Fig. 2. The parameter fault θ (dotted) and its estimation $\hat{\theta}$ (solid).