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# Robust Fault Diagnosis for a Class of Nonlinear Systems with Unknown Parameters

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**Abstract**: The fault diagnosis problem for a class of nonlinear systems with unknown parameters in both states and inputs is discussed. Under some geometric conditions, the systems are transformed into two different subsystems. One is not affected by actuator faults, so the nonlinear adaptive observer and the parameter adaptive law can be designed. The other whose states can be measured is affected by the faults. The observation scheme is then used for model-based monitoring and fault diagnosis. Selection of threshold is investigated. Finally, a numerical example is used to illustrate the applicability of the proposed method.

**Key words**: fault detection and isolation; nonlinear systems; adaptive observer; unknown parameters
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# 一类具有未知参变量的非线性系统的鲁棒故障诊断

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**摘要**: 讨论了一类含有状态和输入未知参变量的非线性系统的故障诊断问题.在满足一些几何条件的情况下,该类系统可化成两类不同的子系统.对于其中一类不受故障影响的子系统,得到了其非线性自适应观测器及参数自适应律的设计;另一类受故障影响的子系统的状态是可测的,给出了该类子系统的基于模型监测和故障诊断的观测方案.然后,给出了用于验证本文所提方案的数字示例.

**关键词**: 故障诊断及隔离; 非线性系统; 自适应观测器; 未知参变量

## 1 Introduction

Owing to the increasing demand for high reliability for many industrial processes, fault detection and isolation (FDI) algorithms and their applications to a wide range of industrial processes have been the subjects of intensive investigation over the past two decades. Fruitful results can be found in several excellent survey papers[1~6] and books[7~9]. Various model-based methods for the FDI have been developed. Among them, the observer-based FDI technique is one of the important schemes.

However, most research work on FDI have been concentrated on linear systems, and only limited results for nonlinear systems were obtained. In [10] FDI for bilinear systems without any uncertainties was discussed. Fault diagnosis for a class of nonlinear systems using disturbance decoupling principle was investigated in [11]. But in some cases, the perfect disturbance decoupling from faults or residual is not possible (see [12,13] for example), so robust or adaptive observers are needed to be designed for FDI. More recently, some results on FDI for special classes of nonlinear systems are available (e.g. [14~16]).

In this paper, we consider the FDI problem for a class of nonlinear systems with unknown parameters in both

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states and inputs. At first, under some geometic conditions, the system is transformed into two subsystems. The first subsystem is in the so called adaptive observer canonical form which is decoupled from actuator fault. The other is affected by the fault, but its states can be measured directly. As a generalization of the observer design approach in [17, 18], an adaptive observer design is proposed for the first subsystem. By using the estimation of both states and parameters, we can approximate the fault by discretizing the second subsystem. Selection of threshold with reliability is discussed.

This paper is organized as follows. Section 2 gives geometric conditions for the existence of a transformation that transforms the original uncertain system into a desired form. Then an adaptive observer design and parameter adaptive law are given based on the transformed system. In Section 3, actuator fault detection and isolation are discussed. Release of SPR requirement is discussed in Section 4. A numerical example is included in Section 5, followed by some concluding remarks in Section 6.

## 2 Adaptive observer design

Consider the following nonlinear system with unknown parameters

$$\dot{x} = f(x) + q_0(x)u + \sum_{i=1}^{p}\theta_i q_i(x,u) + \sum_{j=1}^{d} e_j(x) f_{aj}, \tag{1}$$

$$y = h(x) = [h_1(x),\cdots,h_l(x),h_{l+1}(x),\cdots,h_r(x)], \tag{2}$$

where the state is $x \in \mathbb{R}^n$, the input is $u \in \mathbb{R}^m$. and the output is $y \in \mathbb{R}^r$. The fault $f_a = [f_{a1},\cdots,f_{ad}] \in \mathbb{R}^d$ is modeled as an additional disturbance input with $d \leqslant r < n$, and the unknown parameter is $\theta = [\theta_1,\cdots,\theta_p] \in \mathbb{R}^p$. Furthermore, $f(\cdot)$, $q_0(\cdot)$ and $q_i(\cdot,\cdot)(i = 1,\cdots,p)$ are smooth vector fields, and $h(\cdot)$ is a smooth vector function. The failure representation formulation given in (1) and (2) does not address sensor faults. The description of a sensor fault requires an additional term in the output equation. The construction and analysis of sensor fault diagnosis architectures require further investigation.

**Remark 1** According to [7 ~ 9], there are two kinds of faults. One is in additive form, the other is in multiplicative form. The fault description in this paper belongs to the former.

**Definition** The adaptive observer canonical form (AOCF) of system (1) and (2) is described as

$$\dot{z} = \begin{bmatrix} 0_{l\times l} & 0_{l\times(n-l)} \\ 0_{(n-l)\times l} & A_0 \end{bmatrix} z + \gamma(y,u) + \sum_{i=1}^{p}\psi_i(y,u)\theta_i + \sum_{j=1}^{d}\phi_j(z) f_{aj}, \tag{3}$$

$$y = \begin{bmatrix} I_{l\times l} & 0_{(r-l)\times l} \\ 0_{(n-l)\times l} & C_0 \end{bmatrix} z, \tag{4}$$

where

$$A_0 = \mathrm{diag}[A_1,\cdots,A_{r-l}],\ C_0 = \mathrm{diag}[C_1,\cdots,C_{r-l}],$$

$$A_i = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \end{bmatrix},\ 1 \leqslant i \leqslant r-l,$$

$$C_i = [1\ \ 0\ \ \cdots\ \ 0],\ 1 \leqslant i \leqslant r-1,$$

$$\phi_j^{\mathrm{T}} = [\,*\cdots*\ \underbrace{0\cdots0}_{n-1}],\ j = 1,\cdots,d.$$

For the sake of completeness, we list out below the standard Lie derivative notations of differential geometry [19], which will be used in Assumption 1 and Lemma 1.

1) The differential of a smooth function $h:\mathbb{R}^n \to \mathbb{R}$ is denoted by

$$\mathrm{d}h = \left[\frac{\partial h}{\partial x_1}\ \ \cdots\ \ \frac{\partial h}{\partial x_n}\right].$$

2) The Lie derivative of a function $h$ along a vector field $f$ is denoted by $L_f h = \mathrm{d}h \cdot f$ and recursively as

$$L_f^n h = L_f(L_f^{n-1}h) = \mathrm{d}(L_f^{n-1}h)\cdot f.$$

3) The Lie bracket of two vector fields $f, g:\mathbb{R}^n \to \mathbb{R}^n$ is denoted by

$$[f,g] = \frac{\partial f}{\partial x}\cdot g - \frac{\partial g}{\partial x}\cdot f.$$

The Lie bracket of $f$ and $g$ is also denoted by $ad_f g$, which leads to recursive Lie bracket notation

$$ad_f^m g = ad_f(ad_f^{m-1}g).$$

4) The relative degree of $h_i(i = 1,\cdots,r)$ for the system described by (1) and (2) are denoted by

$$\rho_i = \min\{s \mid L_{q_{0_j}} L_f^{s-1} h_i(x) \neq 0,\ j = 1,\cdots,m\}.$$

**Assumption 1** $\rho_1 = \cdots = \rho_l = \sum_{i=1}^{r}\rho_i = n$, and the system is locally observable, i.e.

$$\mathrm{rank}\{\mathrm{d}h_i(x),\cdots,\mathrm{d}(L_f^{\rho_i-1}h_i):1 \leqslant i \leqslant r\} = n,$$

where $\rho_i(i = 1,\cdots,r)$ is the relative degree of $h_i(x)$.

**Lemma 1** Under Assumption 1, there exists a global diffeomorphism $z = N(x)$ with $N(0) = 0$ and $z \in \mathbb{R}^n$, transforming 1) and 2) into AOCF if and only if i) there exist $r$ vector fields $g_1, \cdots, g_r$ satisfying

$$L_{g_s} L_f^{k-1} h_t = \delta_{s,t} \delta_{k,\rho_t},$$

for $1 \leqslant s \leqslant r, 1 \leqslant k \leqslant \rho_t, 1 \leqslant t \leqslant r$,
with $\delta_{s,t} = 0$ for $s \neq t$, and $\delta_{s,s} = 1$, such that

$$[ad_f^i g_s, ad_f^j g_t] = 0,$$

for $1 \leqslant s, t \leqslant r, 0 \leqslant i \leqslant \rho_s - l, 0 \leqslant j \leqslant \rho_t - l$.

ii) the vector fields

$$ad_f^i g_s,\ 1 \leqslant s \leqslant r,\ 0 \leqslant i \leqslant \rho_i - 1.$$

are complete.

iii) $[q_i, ad_f^j g_s] = 0$, for $0 \leqslant i \leqslant p, 0 \leqslant j \leqslant \rho_s - 1, 1 \leqslant s \leqslant r$.

iv) $e_j = \sum_{i=1}^{l} \phi_{ji}(z) g_i$ for $j = 1, \cdots, d$.

Proof According to [17], conditions i) and ii) are necessary and sufficient for 1) and 2) (with $\theta = 0$ and $f_a = 0$) to be transformable via a global diffeomorphism $z = N(x)$ into

$$\dot{z} = \begin{bmatrix} 0_{l\times l} & 0_{l\times(n-l)} \\ 0_{(n-l)\times l} & A_0 \end{bmatrix} z + \gamma(y, u),$$

$$y = \begin{bmatrix} I_{l\times l} & 0_{(r-l)\times l} \\ 0_{(n-l)\times l} & C_0 \end{bmatrix} z,$$

where the change of coordinates is defined by

$$ad_f^i g_s = (-1)^i \frac{\partial}{\partial z_s^{i+1}},\ 0 \leqslant i \leqslant \rho_s - 1,\ 1 \leqslant s \leqslant r.$$

Condition iii) guarantees that $q_i$ only depends on $y$ and $u$ in the $z$-coordinates. Condition iv) is necessary and sufficient to transform $e_j$ into $\phi_j$ whose last $n - l$ elements zero in $z$-coordinates. Thus system (1) and (2) can be transformed into (3) and (4) under the conditions i) ~ iv). This completes the proof.

Denote

$$z^1 = [z_1, \cdots, z_l]^{\mathrm{T}},\ z^2 = [z_{l+1}, \cdots, z_n]^{\mathrm{T}};$$

$$y^1 = [y_1, \cdots, y_l]^{\mathrm{T}},\ y^2 = [y_{l+1}, \cdots, y_r]^{\mathrm{T}}.$$

then system (3) and (4) can be rewritten as

$$\dot{z}^1 = \gamma^1(y, u) + \psi^1(y, u)\theta + M(z) f_a, \quad (5)$$

$$y^1 = z^1, \quad (6)$$

$$\dot{z}^2 = A_0 z^2 + \gamma^2(y, u) + \psi^2(y, u)\theta, \quad (7)$$

$$y^2 = C_0 z^2, \quad (8)$$

where

$$M(z) = \begin{bmatrix} L_{e_1} h_1 & \cdots & L_{e_d} h_1 \\ \vdots & \cdots & \vdots \\ L_{e_1} h_l & \cdots & L_{e_d} h_l \end{bmatrix}, \quad (9)$$

**Remark 2** As a result of the transformation, it is clear that in (5) ~ (8), the actuator faults enter only through the first subsystem whose states can be directly measured, while the second subsystem is not affected by any faults. This enables us to design adaptive observer for the second subsystem which will be used for fault diagnosis. The construction of fault diagnosis architecture for faults whose distribution does not satisfy condition iv) in Lemma 1 needs further investigation.

**Remark 3** The unknown parameter $\theta$ still exists in transformed system described by (5) and (7). This improves existing results of FDI for nonlinear systems in [11] where a perfect decoupling of system uncertainty is required.

**Assumption 2** There exist $B$ and $\bar{\psi}^2(y, u)$ such that $\psi^2(y, u) = B\bar{\psi}^2(y, u)$. Furthermore, $C_0[sI - (A_0 - KC_0)]^{-1}B$ is strictly positve real.

**Remark 4** The Strictly positve real requirement in the above assumption is equivalent to the following:
For a given positive definite matrix $Q > 0$, there exists $P > 0$, such that

$$(A_0 - KC_0)^{\mathrm{T}} P + P(A_0 - KC_0) = -Q, \quad (10)$$

$$PB = C_0^{\mathrm{T}}. \quad (11)$$

**Theorem 1** Under Assumption 2, there exists a stable adaptive observer for system (7) and (8), and the adaptive observer is given by

$$\dot{\hat{z}}^2 = A_0 \hat{z}^2 + \gamma^2(y, u) + B\bar{\psi}^2(y, u)\hat{\theta} + K(y^2 - C_0 \hat{z}^2), \quad (12)$$

with the parameter update law

$$\dot{\tilde{\theta}} = -G\bar{\psi}^2(y, u) C_0 \tilde{z}^2, \quad (13)$$

where $\tilde{\theta} = \theta - \hat{\theta}, \tilde{z}^2 = z^2 - \hat{z}^2$, and $G$ is a positive definite weighting matrix.

Proof From (7) and (12), the observer error dynamics is

$$\dot{\tilde{z}}^2 = (A_0 - KC_0)\tilde{z}^2 + B\bar{\psi}^2(y, u)\tilde{\theta}. \quad (14)$$

The Lyapunov function is chosen as

$$V = (\tilde{z}^2)^{\mathrm{T}} P \tilde{z}^2 + \tilde{\theta}^{\mathrm{T}} G^{-1} \tilde{\theta}, \quad (15)$$

where $P$ is the positive definite solution of (10) and (11), and $G$ is a positive definite weighting matrix.

From (13) ~ (15), we can obtain

$$\dot{V} = -(\tilde{z}^2)^{\mathrm{T}} Q \tilde{z}^2 + 2\tilde{\theta}^{\mathrm{T}}[\tilde{z}^2 PB \bar{\psi}^2(y,u) + G^{-1}\dot{\tilde{\theta}}] = -(\tilde{z}^2)^{\mathrm{T}} Q \tilde{z}^2, \quad (16)$$

which proves the stability of origin $\tilde{z}^2 = 0, \tilde{\theta} = 0$ and the boundedness of $\tilde{z}^2(t)$ and $\tilde{\theta}(t)$. From (14), $\dot{\tilde{z}}$ is bounded as well. According to Barbalat's Lemma[20], one can get

$$\lim_{t \to \infty} \tilde{z}^2(t) = 0. \quad (17)$$

This completes the proof.

**Remark 5** It is well known in adaptive control that a persistently exciting signal can guarantee unbiased estimation. Therefore, to obtain an accurate estimation of unknown parameter $\theta$, i.e. $\lim_{t \to \infty} \hat{\theta} = \theta$, a persistently exciting signal may be required in practice.

**Remark 6** Theorem 1 generalized the existing result of adaptive observer design in [18] where the single output system without actuator fault was considered.

## 3 Fault detection and isolation

For our result, we need to make the following assumption:

**Assumption 3** rank $M(z) = d$, where $M(z)$ is defined in (9).

**Remark 7** Assumption 3 is an extension of the assumption rank $CE$ = rank $E$ which is necessary for FDI of linear systems.

Discretizing subsystem (5) and (6) yields

$$TM(z(k))f_a(k) = y^1(k+1) - y^1(k) - T[\gamma^1(y(k),u(k)) + \psi^1(y(k),u(k))\theta(k)], \quad (18)$$

where $k$ represents the $k$-th time step and $T$ is the sampling period. Assuming that no fault occurs during the initial transient of the observer, using the estimation $\hat{z}^2(k), \hat{\theta}$ for $z^2(k)$ and $\theta(k)$ to approximate the actuator fault as

$$\hat{f}_a(k) = (\hat{M}^{\mathrm{T}}\hat{M})^{-1}\hat{M}^{\mathrm{T}}[\frac{y_1(k+1) - y^l(k)}{T} - \gamma^1(y(k),u(k)) - \psi^1(y(k),u(k))\hat{\theta}(k)], \quad (19)$$

where $\hat{M}(k) = M(y^1(k), \hat{z}^2(k))$.

Let

$$N(k) = (M^{\mathrm{T}}M)^{-1}M^{\mathrm{T}}(y^1(k), z^2(k)),$$
$$\hat{N}(k) = (M^{\mathrm{T}}M)^{-1}M^{\mathrm{T}}(y^1(k), \hat{z}^2(k)),$$

one can have

$$f_a(k) - \hat{f}_a(k) = (N(k) - \hat{N}(k)) \cdot \left[\frac{y^1(k+1) - y^1(k)}{T} - \gamma^1(y(k),u(k))\right] + (N(k) - \hat{N}(k))\psi^1(y(k),u(k))\hat{\theta}(k) + \hat{N}(k))\psi^1(y(k),u(k))(\theta(k) - \hat{\theta}(k)). \quad (20)$$

Note that faults are not involved in the process of estimating $z^2, \theta$. Hence $\hat{N} \to N$ if $\hat{z}^2(k) \to z^2(k)$. If the unknown parameter $\theta(k)$ is bounded, then for given $\varepsilon > 0$, there exists $K$ such that for $k > K$

$$\| (N(k) - \hat{N}(k))[\frac{y^1(k+1) - y^1(k)}{T} - \gamma^1(y(k),u(k)) + \psi^1(y(k),u(k))\hat{\theta}(k)] \| \leq \varepsilon. \quad (21)$$

On the other hand, from the proof of Theorem 1, $\tilde{\theta}$ is bounded. So there exists $L > 0$, such that

$$\| \hat{N}(k)\psi^1(y(k),u(k))\tilde{\theta}(k) \| \leq L\sqrt{\lambda_{\max}(\hat{N}^{\mathrm{T}}\hat{N})}. \quad (22)$$

Therefore

$$\| f_a - \hat{f}_a \| \leq L\sqrt{\lambda_{\max}(\hat{N}^{\mathrm{T}}\hat{N})} + \varepsilon. \quad (23)$$

Threshold value is defined as

$$T_r(k) = L\sqrt{\lambda_{\max}(\hat{N}^{\mathrm{T}}\hat{N})} + \varepsilon. \quad (24)$$

When $\| \hat{f}_a(k) \| > T_r(k)$, then the alarm for faults is on, otherwise, the alarm is off.

**Remark 8** Since the threshold is greater than the error of the fault estimation, the FDI process is reliable.

**Remark 9** FDI by means of adaptive nonlinear observer was also studied in [21,22]. The advantage of our method is that it can detect not only the occurance but also the amplitude of faults. Learning-based fault diagnosis for nonlinear systems was devloped in [14]. However, the strict assumption that all the state variables are available for measurement is required.

## 4 Discussion on release of the SPR requirement

In Section 2, the stable adaptive observer design is under the assumption 2 that the plant transfer function is strictly positive real (SPR), which does not always hold in practice. In this section, we discuss the possibility of removing the SPR requirement. For the sake of simplicity, we assume that the subsystem described by (7) and (8) is single output, that is, $r = l + 1$, the obtained results can be extended to the case of multiple outputs.

Define $\varepsilon(t) = y^2(t) - \hat{y}^2(t)$, using the same observer in (12), we can obtain the following input-output expression of error equation

$$\varepsilon(t) = H(s)\bar{\psi}^2(y,u)\tilde{\theta}(t), \tag{25}$$

where $H(s) = C_0[sI - (A_0 - KC_0)]^{-1}B$. Using the augmented error technique in [20], it can be shown that

$$\varepsilon(t) = \tilde{\theta}^{\mathrm{T}}(t)\xi(t) + H(s)\bar{\psi}^2(y,u)\hat{\theta}(t) - \hat{\theta}(t)H(s)\bar{\psi}^2(y,u) + \delta(t), \tag{26}$$

where $\xi = H(s)\bar{\psi}^2(y,u)$, $\delta(t)$ decays exponentially and can be neglected. We can define

$$\varepsilon_1(t) = \varepsilon(t) - [H(s)\bar{\psi}^2(y,u)\hat{\theta}(t) - \hat{\theta}(t)H(s)\bar{\psi}^2(y,u)] \tag{27}$$

as the augmented error signal. Therefore, it can be obtained that

$$\varepsilon_1(t) = \tilde{\theta}^{\mathrm{T}}(t)\xi(t). \tag{28}$$

Equation (28) is in the standard form of the error equations widely used in adaptive control theory[20]. The adaptive updating laws used in adaptive control can be directly applied to tune $\tilde{\theta}(t)$. This can be summarized in the following theorem.

**Theorem 2** With error model (28) and the fact that $H(s)$ is stable, the parameter update law

$$\dot{\tilde{\theta}} = -G\frac{\varepsilon_1(t)\xi(t)}{1+\xi^{\mathrm{T}}(t)\xi(t)} \tag{29}$$

realizes a bounded $\tilde{\theta}(t)$ and $\dot{\tilde{\theta}}(t) \in L^2$, furthermore, equation (17) holds.

Proof The proof of this theorem is omitted since the same formulations presented in [20] can be applied.

## 5 An illustrative example

Consider the following nonlinear system with known parameters

$$\begin{cases} \dot{x}_1 = x_2 - x_1\theta, \\ \dot{x}_2 = x_2x_3 + (x_1 + x_1e^{x_2})f_a, \\ \dot{x}_3 = x_1 - u + (1 + e^{x_2})f_a + x_3\theta, \\ y_1 = x_1, \\ y_2 = x_3. \end{cases} \tag{30}$$

By simple calculation, one can conclude that all the assumptions in Theorem 1 hold. In fact, the relative degree $\rho_1 = 1, \rho_2 = 2$.

The transformation $z = N(x)$ is described as

$$\begin{cases} z_1 = x_1, \\ z_2 = x_2 - x_1x_3, \\ z_3 = x_3. \end{cases} \tag{31}$$

Under this transformation, the nonlinear system (30) is changed into the following AOCF

$$\begin{cases} \dot{z}_1 = z_2 + y_1y_2 - y_1\theta, \\ \dot{z}_2 = -y_1^2 + y_1u, \\ y_1 = z_1. \end{cases} \tag{32}$$

$$\begin{cases} \dot{z}_3 = y_1 - u + y_2\theta + (1 + e^{z_2})f_a, \\ y_2 = z_3. \end{cases} \tag{33}$$

Note that the subsystem (32) can be written as

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} + \begin{bmatrix} y_1y_2 \\ -y_1^2 \end{bmatrix} + \begin{bmatrix} 0 \\ y_1 \end{bmatrix}u + \begin{bmatrix} -y_1 \\ 0 \end{bmatrix}\theta, \tag{34}$$

$$y_1 = \begin{bmatrix} 1 & 0 \end{bmatrix}\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}. \tag{35}$$

It is evident that Assumption 2 holds. Therefore, the stable adaptive observer for subsystem (34) and (35) can be designed according to (12). Furthermore, the actuator fault $f_a(k)$ can be detected and isolated if $\| f_a(k) \| > T_r(k)$ with $T_r(k)$ as defined by (24).

In the simulation, the actuator faults cosidered are respectively as follows

$$f_a(t) = \begin{cases} 0, & \text{for } 0 \leqslant t \leqslant 1, \\ 0.4, & \text{for } 1 < t \leqslant 5, \end{cases} \tag{36}$$

$$f_a(t) = 1 + \sin(4\pi t),\ 0 \leqslant t \leqslant 5. \tag{37}$$

The gain matrix $K$ is selected to be $[7 \quad 12]^{\mathrm{T}}$, the sampling period is 0.01s, and the weighting matrix $G = 10$. Fig.1 shows the response of the observer when there is an actuator fault described by (36) in the system. Fig.2 illustrates the estimation of the actuator fault. Fig.3 and 4 depict corresponding results of actuator fault described by (37). It is shown that good fault estimation is achieved despite the unknown parameter in the system.

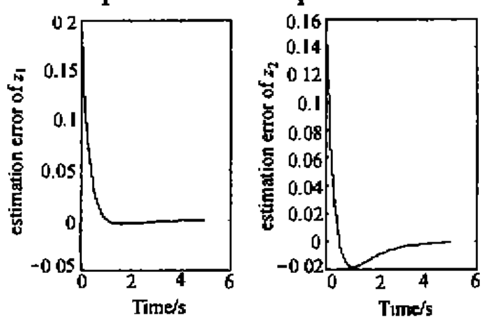


Fig.1 State estimation under fault occurance

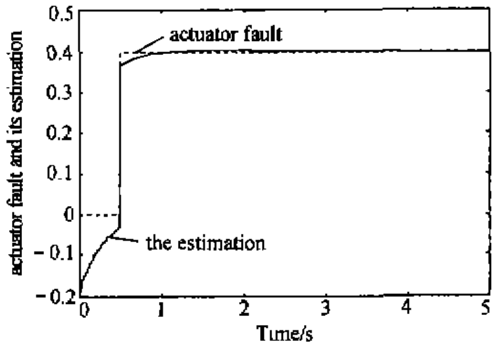


Fig. 2 Fault identification and the estimation

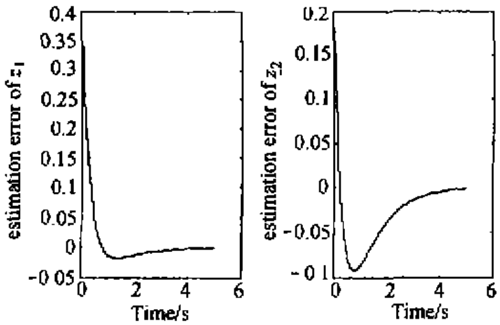


Fig. 3 State estimation under fault occurance

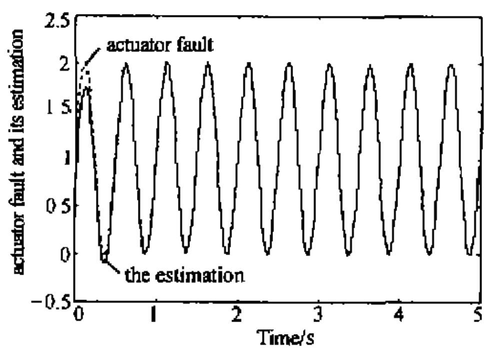


Fig. 4 Fault identification and the estimation

## 6 Conclusion

This fault diagnostic approach in this paper uses an adaptive observer to detect and identify actuator faults for nonlinear systems with unknown parameters. A numerical example is given to illustrate the proposed scheme.

FDI for more general nonlinear systems with application to practical systems will be investigated in future.

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