

Fault Detection by Using an Adaptive Observer

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Abstract: In this paper, a design method to detect faults in plants with uncertainties is proposed. When a plant has faults, the plant will be corrupted by an unknown fault signal. In addition, the plant also includes uncertainties, such as disturbances and plant parameter deviations. In this case, the proposed method estimates the fault signal by using an adaptive observer. Numerical examples are given to demonstrate the validity of the proposed method.

Keywords: Fault detection, adaptive observer, uncertainty, unknown fault signal

1. INTRODUCTION

When a disaster or an accident occurs in a plant, it is important to obtain the abnormal condition of the plant or the faults in the plant. Also, it is inevitable to discover where the malfunction occurs at an early stage, even when the whole plant seems to be normal. This case is indispensable to recover the damage of malfunction. For this reason, faults diagnosis or faults detection technology of the plant is studied by many researchers[1]. There are 2 ways of methods to detect faults in a plant. One method is a mechanical method that uses increased number of the sensors. The other one is an analytical method that processes information of the plant [2]. Mainly the analytical methods are studied because that the mechanical method costs more than the analytical method.

The analytical methods[3] are classified into 2 categories. One is to use a model of the plant and the other is not to use the model of the plant. In the latter case, there are two methods of using a neural network or a genetic algorithm applied to artificial intelligence [8]. On the other hand, the first method uses a static model or a dynamic model. As the static methods, there are parity vector law, vector slope law, probability model to a static mode. The most commonly used method that uses a dynamic model is the method that uses an observer. The method that uses an observer detects the faults signal into the plant by the state estimation observer composed by a dynamic model of the plant. Among them, there is a method that uses plural observers[4] and a method that uses a disturbance observer[5]. In the case that the observed plant has an unknown modeled part, the method that detects faults signal without being influenced by uncertainty of the plant is proposed[6]. The observer in this method needs to be not influenced by uncertainty of the plant, but to be influenced to the faults signal. Also, a method using the adaptive observer which identify uncertainty of the plant is proposed[7].

In this paper, we propose a method to estimate the fault

signal by using an unknown-input state observer. In this case, the considered plant includes uncertainties, such as disturbances or plant parameter deviations. The proposed observer estimates the uncertainties and also identifies the plant parameters while fault detection works.

The paper is organized as follows. In Section 2 we state the problem setup. Section 3 gives the fault detection scheme for the case of plant without uncertainty by using disturbance observer. For the case of plant with uncertainty, a fault detection scheme by using an adaptive observer is given in Section 4. Examples on plants with uncertainties are illustrated in Section 5 to show the proposed method.

2. PROBLEM FORMULATION

Consider the following plant with uncertainty $Gg(u, t, \theta)$

$$\dot{x}(t) = Ax(t) + Bu(t) + Ff(t) + Gg(u, t, \theta) \quad (1)$$

$$y(t) = Cx(t) \quad (2)$$

where, $x \in R^n$ denotes the state vector and is unobservable. $u \in R^r$ and $y \in R^m$ are the measurable control input vector and the measurable output vector, respectively. A, B, C, F and G are known matrices with appropriate dimensions.

$f(t) \in R^p$ represents the fault vector which is considered as an unknown time function. In this paper, if there exists fault, then $f(t) \neq 0$, otherwise $f(t) = 0$. $g(u, t, \theta) \in R^l$ is the unknown disturbance vector satisfied the following relation when it is scalar.

$$g(u, t, \theta) = \sum_{i=1}^l \varphi_i(u, t)\theta_i = \varphi^T(u, t)\theta \quad (3)$$

$$\varphi(u, t) = [\varphi_1(u, t), \dots, \varphi_l(u, t)]^T \quad (4)$$

$$\theta = [\theta_1, \dots, \theta_l]^T \quad (5)$$

where, $\varphi(u, t)$ is known and θ in unknown vector. In the case of $g(u, t, \theta) \in R^l$, we have $\varphi(u, t) \in R^{l \times l}$. The objective is to estimate θ and $f(t)$ by using adaptive observer. In the following section, a fault detection scheme for the case of plant without uncertainty by using disturbance observer is shown.

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3. FAULT DETECTION SCHEME USING DISTURBANCE OBSERVER

In this section, for the case of $Gg(\mathbf{u}, t, \boldsymbol{\theta}) = 0$ a fault detection scheme by using disturbance observer is discussed. In this case, from (1) and (2) we have

$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B\mathbf{u}(t) + F\mathbf{f}(t) \quad (6)$$

$$\mathbf{y}(t) = C\mathbf{x}(t) \quad (7)$$

Then it is well known from the existing disturbance observer design scheme [9] that the following augmented system concerning fault signal $\mathbf{f}(t)$ and the state of (1) can be obtained, where $\mathbf{f}(t)$ is an unknown constant.

$$\dot{\mathbf{x}}_e(t) = A_e\mathbf{x}_e(t) + B_e\mathbf{u}(t) \quad (8)$$

$$\mathbf{y}_a(t) = C_e\mathbf{x}_e(t) \quad (9)$$

$$\mathbf{x}_e(t) \triangleq \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{f}(t) \end{bmatrix} \quad (10)$$

$$A_e \triangleq \begin{bmatrix} A & F \\ 0 & 0 \end{bmatrix} \quad (11)$$

$$B_e \triangleq \begin{bmatrix} B \\ 0 \end{bmatrix} \quad (12)$$

$$C_e \triangleq \begin{bmatrix} C & 0 \\ 0 & 0 \end{bmatrix} \quad (13)$$

where, the state observer is obtained as follows.

$$\dot{\hat{\mathbf{x}}}_e(t) = A_e\hat{\mathbf{x}}_e(t) + B_e\bar{\mathbf{u}}(t) - K_e\boldsymbol{\varepsilon}(t) \quad (14)$$

$$\hat{\mathbf{y}}_1(t) = C_e\hat{\mathbf{x}}_e(t) \quad (15)$$

$$\boldsymbol{\varepsilon}(t) \triangleq \hat{\mathbf{y}}_1(t) - \mathbf{y}_a(t) \quad (16)$$

$$\hat{\mathbf{x}}_e(t) \triangleq \begin{bmatrix} \hat{\mathbf{x}}(t) \\ \hat{\mathbf{f}}(t) \end{bmatrix} \quad (17)$$

$$\mathbf{u}(t) = \bar{\mathbf{u}}(t) - \hat{\mathbf{u}}(t)$$

where the augmented system is observable and K_e is selected such that matrix $A_0 = A_e - K_eC_e$ is stable. As a result, the fault signal $\mathbf{f}(t)$ can be estimated by the above state observer.

In practice, uncertainties problem arises frequently when plant model receives the effect of uncertainties caused by disturbances or the variation of parameters values. In this case, the above-mentioned design scheme can not work well. In the following, a fault detection scheme for the case of plant with uncertainty by using an adaptive observer is given.

4. FAULT DETECTION SCHEME USING ADAPTIVE OBSERVER

As an extension of the result in Section 3, the uncertainty of the plant is considered as $Gg(\mathbf{u}, t, \boldsymbol{\theta})$ in (1). A fault detection scheme for plant (1) is given by using an adaptive observer. Using the same manner with (8), the following augmented system concerning fault signal $\mathbf{f}(t)$ and the state of (1) can be obtained in the case of $Gg(\mathbf{u}, t, \boldsymbol{\theta}) \neq 0$.

$$\dot{\mathbf{x}}_e(t) = A_e\mathbf{x}_e(t) + B_e\mathbf{u}(t) + \bar{G}\bar{g}(\mathbf{u}, t, \boldsymbol{\theta}) \quad (18)$$

$$\mathbf{y}_a(t) = C_e\mathbf{x}_e(t) \quad (19)$$

where

$$\bar{g}(\mathbf{u}, t, \boldsymbol{\theta}) \triangleq \begin{bmatrix} g \\ 0 \end{bmatrix} \quad (20)$$

$$\bar{G} \triangleq \begin{bmatrix} G & 0 \\ 0 & 0 \end{bmatrix} \quad (21)$$

and $\bar{g} \in R^{(l+n)}$ and $\bar{G} \in R^{(l+n)}$.

Define the estimate of $\boldsymbol{\theta}$ as $\hat{\boldsymbol{\theta}}$, using the estimate we can design adaptive observer as follows.

$$\dot{\hat{\mathbf{x}}}_e(t) = A_e\hat{\mathbf{x}}_e(t) + B_e\bar{\mathbf{u}}(t) - K_e\boldsymbol{\varepsilon}(t)$$

$$\hat{\mathbf{y}}_1(t) = C_e\hat{\mathbf{x}}_e(t) \quad (22)$$

$$\boldsymbol{\varepsilon}(t) \triangleq \hat{\mathbf{y}}_1(t) - \mathbf{y}_a(t)$$

where

$$\hat{\mathbf{u}} = \hat{g}$$

$$\hat{g} = g(\mathbf{x}, \mathbf{u}, t, \hat{\boldsymbol{\theta}}) = \boldsymbol{\varphi}(\mathbf{u}, t)\hat{\boldsymbol{\theta}}$$

$$\mathbf{u}(t) = \bar{\mathbf{u}}(t) - \hat{\mathbf{u}}(t)$$

In this paper, for the simplicity it is assumed that $B = G$. The following parameter adjusting law is given to estimate the unknown parameter $\boldsymbol{\theta}$.

$$\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}_I + \hat{\boldsymbol{\theta}}_P \quad (23)$$

$$\dot{\hat{\boldsymbol{\theta}}}_I(t) = -\Gamma_I\boldsymbol{\varphi}(\mathbf{u}, t)(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \quad (24)$$

$$\hat{\boldsymbol{\theta}}_P(t) = -\Gamma_P\boldsymbol{\varphi}(\mathbf{u}, t)(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \quad (25)$$

where $\Gamma_I \geq 0$ and $\Gamma_P > 0$ are adjusting gain matrix. The augmented error system is shown as follows.

$$\dot{e}(t) = A_0e(t) + G(g(\mathbf{u}, t, \hat{\boldsymbol{\theta}}) - g(\mathbf{u}, t, \boldsymbol{\theta})) \quad (26)$$

$$e(t) = \hat{\mathbf{x}}_e(t) - \mathbf{x}_e(t) \quad (27)$$

$$\boldsymbol{\varepsilon}(t) \triangleq C_e e(t) \quad (28)$$

provided that the transfer function between $(g(\mathbf{u}, t, \hat{\boldsymbol{\theta}}) - g(\mathbf{u}, t, \boldsymbol{\theta}))$ and $\boldsymbol{\varepsilon}(t)$ is strictly positive real and the error system is observable. As a result, we have $\boldsymbol{\varepsilon}(t) \rightarrow 0$ [9] and $e(t) \rightarrow 0$. Further, the fault signal $\mathbf{f}(t)$ can be estimated by the above adaptive observer.

5. SIMULATION EXAMPLES

In this section, to illustrate the proposed method developed and analyzed in Section 4, two simulation examples are considered.

5.1. Example 1

Consider a continuous time-invariant single-input single-output unstable plant.

$$\begin{cases} \dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B(\mathbf{u}(t) + g(t)) + F\mathbf{f}(t) \\ \mathbf{y}(t) = C\mathbf{x}(t) \end{cases} \quad (29)$$

where

$$A = \begin{bmatrix} 0 & 3 & 2 \\ 1 & 2 & 3 \\ 0 & 2 & 5 \end{bmatrix}$$

$$\begin{aligned}
B &= \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \\
C &= \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \\
F &= \begin{bmatrix} 1 \\ -0.5 \\ 0.5 \end{bmatrix}
\end{aligned} \tag{30}$$

and $u(t)$, $y(t)$ and $f(t)$ are the plant input, plant output and fault signal respectively. $g(t)$ is unknown disturbance signal given as

$$g(t) = \phi^T(t)\theta \tag{31}$$

$\phi^T(t)$ and θ are given by

$$\begin{aligned}
\phi^T(t) &= \begin{bmatrix} \phi_1 & \phi_2 \end{bmatrix} \\
\theta &= \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} \\
&= \begin{bmatrix} 1.0 \\ 1.5 \end{bmatrix}
\end{aligned} \tag{32}$$

In the simulation, $\phi^T(t)$ is known vector and θ is unknown parameter vector. Unknown parameter vector θ is estimated by a parameter adjusting law given in (23) ~ (25). State feedback controller is designed for the plant, \bar{u} is a rectangular wave with period 40. The gain is $K = \begin{bmatrix} 13 & 101 & 226 \end{bmatrix}$, where the desired closed-loop poles are -1 , -2 and -3 . Meanwhile, the fault signal is selected as

$$f(t) = \begin{cases} 0 & t < 30 \\ 0.1 & 30 \leq t < 60 \\ -0.05 & 60 \leq t \end{cases} \tag{33}$$

Based on the design scheme given in Section 4, the gain matrix is derived as $K_e = \begin{bmatrix} 138 & 22.0 & -18.3 & -32.8 \end{bmatrix}$, where the desired closed-loop poles are -5 , -6 , -7 and -10 . The simulation results are shown in Figs. 1 and 2. From Fig. 1, the desired estimate of the fault signal $f(t)$ given in (33) is obtained. Concerning the estimate of parameter vector θ , the estimated values of $\hat{\theta}_1$ (solid line) and $\hat{\theta}_2$ (dashed line) track to 1 and 1.5 (Fig. 1). Meanwhile, from (10) and (17) we know that x_4 in Fig.2 shows the real and estimated fault signals.

5.2. Example 2

Consider the following 2-input 2-output plant.

$$\begin{cases} \dot{x}(t) = Ax(t) + B(u(t) + g(t)) + Ff(t) \\ y(t) = Cx(t) \end{cases} \tag{34}$$

where

$$\begin{aligned}
A &= \begin{bmatrix} 0 & 3 & 4 \\ 1 & 2 & 3 \\ 0 & 2 & 5 \end{bmatrix} \\
B &= \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \\
C &= \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
F &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}
\end{aligned} \tag{35}$$

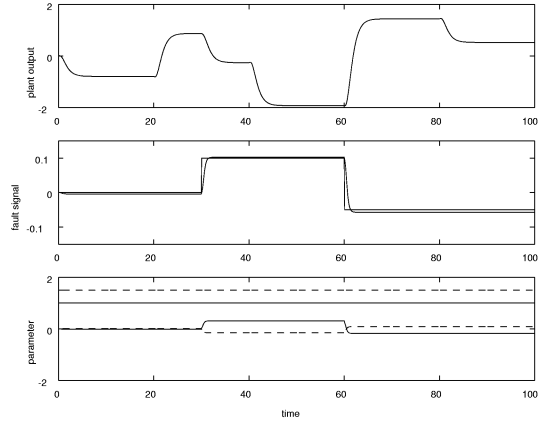


Fig. 1. Time responses of plant output, fault signal and the estimated parameters in Example 1

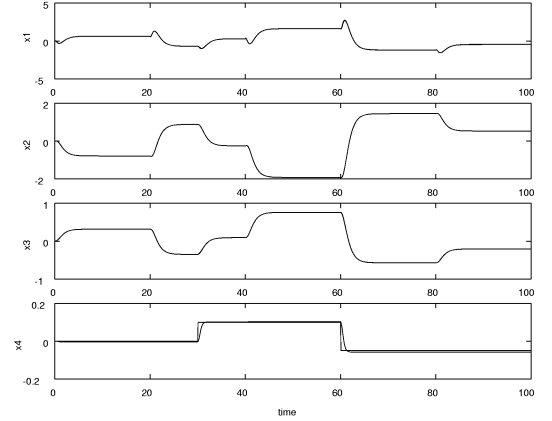


Fig. 2. Time responses of the states in Example 1

and $u(t) = [u_1(t), u_2(t)]^T$, $y(t) = [y_1(t), y_2(t)]^T$ and $f(t) = [f_1(t), f_2(t)]^T$ are the plant input, plant output and fault signal respectively. $g(t)$ is unknown disturbance signal given as

$$g(t) = \phi^T(t)\theta \tag{36}$$

where

$$\begin{aligned}
\phi^T(t) &= \begin{bmatrix} \sin(2t + \pi/2) & 0 \\ 0 & \cos 3t \end{bmatrix} \\
\theta &= \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} \\
&= \begin{bmatrix} 0.5 \\ 1.0 \end{bmatrix}
\end{aligned} \tag{37}$$

In the simulation, $\phi^T(t)$ is known vector and θ is unknown parameter vector. Unknown parameter vector θ is estimated by a parameter adjusting law shown in (23) ~ (25). State feedback controller is designed for the plant. The gain is

$$K = \begin{bmatrix} -2.386 & -1.4466 & -1.1604 \\ 1 & 2 & 3 \\ -1.2022 & -4.5178 & -5.6140 \end{bmatrix} \tag{38}$$

and the desired closed-loop poles are -1 , -2 and -3 . The control input is given as

$$u = u_0 + u_f \tag{39}$$

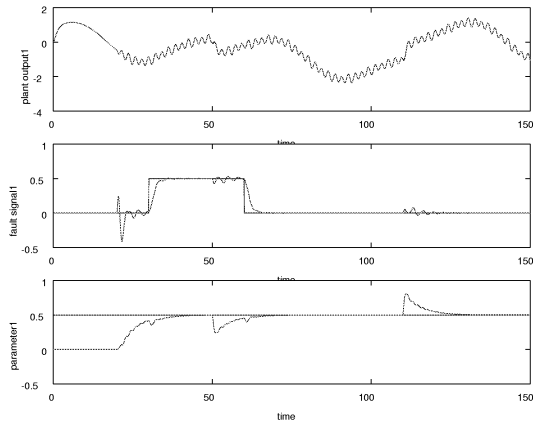


Fig. 3. Time responses of plant output, fault signal and the estimated parameter in Example 2

$$u_0 = \begin{bmatrix} \sin t/5 \\ \cos t/10 \end{bmatrix} \quad (40)$$

The fault signals are selected as

$$f(t) = \begin{bmatrix} f_1(t) \\ f_2(t) \end{bmatrix} \quad (41)$$

$$f_1 = \begin{cases} 0 & t < 30 \\ 0.5 & 30 \leq t < 60 \\ 0 & 60 \leq t \end{cases} \quad (42)$$

$$f_2 = \begin{cases} 0 & t < 50 \\ -0.5 & 50 \leq t < 110 \\ 0 & 110 \leq t \end{cases} \quad (43)$$

Based on the design scheme given in Section 4, the gain matrix is derived as

$$K_e = \begin{bmatrix} 0.6069 & 9.1875 & -5.3952 & 4.1907 & 9.3260 \\ -5.1386 & 2.7014 & -0.1875 & -8.8951 & 4.0234 \end{bmatrix} \quad (44)$$

The desired closed-loop poles are -1 , -2 , -3 , -4 and -5 . The simulation results are shown in Figs. 3 and 4. Fig. 3 shows plant output y_1 , fault signal f_1 and θ_1 . Fig. 4 shows plant output y_2 , fault signal f_2 and θ_2 . From Figs. 3 and 4, the desired estimate of the fault signals $f_1(t)$ and $f_2(t)$ are obtained, where $\Gamma_I = 10.0I$ and $\Gamma_P = 0.8I$. Concerning the estimate of uncertainty-related parameter vector θ , the estimated values of $\hat{\theta}_1$ and $\hat{\theta}_2$ track to the real values 0.5 and 1 (Figs. 3 and 4).

6. CONCLUSION

A design method to detect faults in plants with uncertainties has been proposed. When a plant has faults, the plant will be corrupted by an unknown fault signal. Further, the plant also includes uncertainties, such as disturbances and plant parameter deviations. For the case of plant without uncertainty a fault detection scheme is given by using disturbance observer. For the case of plant with uncertainty, a fault detection scheme by using adaptive observer is shown. Concerning the case of plant with uncertainty, the proposed

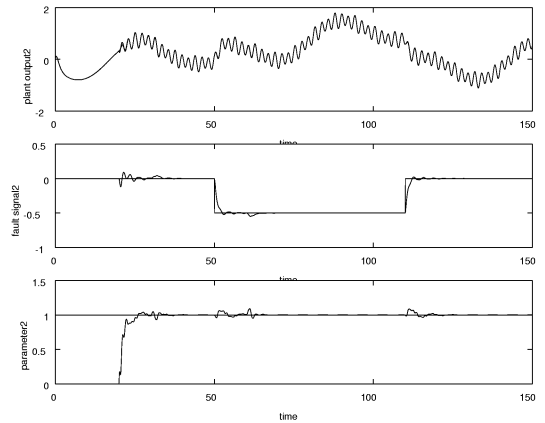


Fig. 4. Time responses of plant output, fault signal and the estimated parameter in Example 2

observer estimates the disturbances and also estimates the plant states while fault detection works. Two examples on plants with uncertainties are illustrated to show the effectiveness of the proposed method.

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