

# THE RESEARCH ON SIMULATION METHOD FOR FAULT DETECTION AND DIAGNOSIS IN SENSORS

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## ABSTRACT

A novel approach based on parameters estimation is presented for fault detection and diagnosis in sensors. Based on known precise parameter of normal working sensors system model is built from real laboratory inputs-outputs data, sequentially residual serial is obtained. Where decision-making rule of detection the fault is given via the use of beys theory, whilst a filter least-square computative algorithm for estimating fault parameters is given. The algorithm is a fast and accurate to calculate value of sensors faults when system model contains noise and sensors outputs contain measured noise. The method can solve both gain type and bias type fault in sensors. Simulated numerical example is included to demonstrate the use of the proposed approaches.

## 1 INTRODUCTION

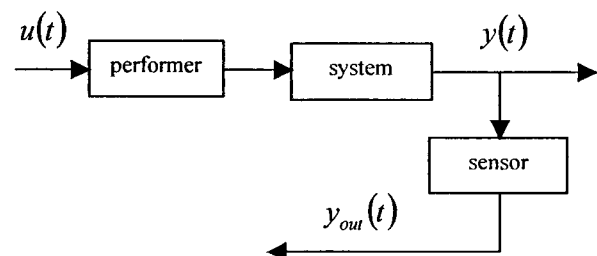
Owing to the increasing demand for high reliability for many industrial processes, fault detection and diagnosis (FDD) algorithms and their application to a wide range of industrial and commercial processes have been the subjects of intensive investigation over the past two decades. The fault of control system contains the fault in system, the fault in actuator and the fault in sensor. But the fault in sensor has the most severe effect on system performance. Like the function of the sense organ of human being, the fault in sensor wont give correct signal if losing it's function so that to bring the paralysis of whole system. It will be a tragedy for an important system. Thus, we can see that it is very import for us to detect the fault in sensors in time. Many methods for sensor fault detection and diagnosis have been developed, and examples include the observer based approaches, neural network based methods, principal component analyses (PCA) based methods etc.

In observer based FDD approaches, observers are constructed based upon a knowledge of the parameter matrices in the state-space representation of the healthy system. This enables fault detection to be performed by checking the observation error in relation to a pre-specified threshold. since the parameter matrices of the system are assumed to be exactly known, difficulties will most certainly arise when applying these methods to practical

systems. This has lead to the use of unknown input observers, where the model uncertainties and slowly varying parameters are treated as unknown inputs to the system. However, these methods are still limited to systems whose dominant parts are linear and known. For faults estimation in sensor these methods only solve alternative between gain and bias type.

Use of neural network can solve problem of sensor fault detection in nonlinear system, but can't estimate value of faults. In addition, the methods has a disadvantage with great account. Now PCA methods interested by researchers most are limited to linear system, it is based on correlative analysis theory, therefore fault detection can be accomplished without system model, as neural network method, in the method, problem of fault estimation can't be solving.

In this situation, a novel simple approach based on parameters estimation is presented for fault detection and diagnosis in sensors. The method can be applied to linear or nonlinear system. First a complexity restricted model was built for the system using the input/output serial when the sensor work normally. Then we can find the residual serial and detect the fault in sensor by using beys decision-making more accurately and fast, whilst algorithm with filter least-square is given to estimate size of fault that is both gain type and bias type occurring in one or more sensors. In the paper, Simulated numerical example is included to demonstrate the use of the proposed approaches. The research work was under normal system condition, namely, the input signal of sensor is correct.



## 2 SYSTEM DESCRIBING

**Fig.1 the system of multi input and output**

Fig.1 is the system of multi input and output, the assumed model is as below:

$$y_i(t) = \theta_{i0} \phi(t-1)^T; \quad (1)$$

$$i = 1, 2, \dots, m$$

$$y(t) = \theta_0 \phi(t-1)^T \quad (2)$$

$y(t)$  means  $m \times 1$  dimension vector of output.

$\phi(t-1)^T$  means  $p \times 1$  dimension matrix constitutes of the former value of  $\{y(t)\}$  and  $\{u(t)\}$ .

$\theta_0$  means  $m \times p$  dimension vector of parameter.

in a general way, the parameter of examining system sensor can be got beforehand, the normal parameter of sensor is assumed to be got, the relation of input and output is satisfied with the equation below,

$$y_{outi}(t) = h_i y_i(t) + b_i + w_i(t) \quad (3)$$

the matrix form can be described,

$$y_{out}(t) = h y(t) + b + W(t) \quad (4)$$

$y_{out}(t)$  means  $m \times 1$  dimension output vector of sensor

$h$  means  $m \times m$  dimension plus diagonal matrix of sensor,  $b$  means  $m \times 1$  dimension bias vector of sensor.

$W(t)$  means zero-average gauss noise.

## 3 FAULT DETECTION

From the theory of parameter estimate, for the determinate system described in formula (2), we can get  $\hat{\theta}$ , the estimate of parameter  $\theta_0$ . So, the one-step output forecaster of main system are as follows,

$$\hat{y}(t) = \hat{\theta} \phi(t-1)^T \quad (5)$$

Then, from formula (4), we get the one-step output forecaster of sensor,

$$\hat{y}_{out}(t) = h \hat{y}(t) + b = h \hat{\theta} \phi(t-1)^T + b \quad (6)$$

build the residual serial of output,  $\tilde{y}_{out}(t) = y_{out}(t) - \hat{y}_{out}(t)$ , it can show that  $\tilde{y}_{out}(t)$  satisfies normal noise, and it is statistical independent. From beys theory, we can get the below algorithm.

The two indexes can be determined on normal work status,

$$\mu_{\tilde{y}_{out0}} = \frac{1}{N_1} \sum_{t=1}^{N_1} \tilde{y}_{outi}(t)$$

$$i = 1, 2, \dots, m \quad (7)$$

$$\sigma_{\tilde{y}_{out0}} = \frac{1}{N_1} \sum_{t=1}^{N_1} [\tilde{y}_{outi}(t) - \mu_{\tilde{y}_{out0}}]^2 \quad (8)$$

suppose the output residual serial of system at time  $k$  changes,

$$\mu_{\tilde{y}_{outik}} = \frac{1}{N} \sum_{t=0}^{N-1} \tilde{y}_{outi}(k-t) \quad (9)$$

$$i = 1, 2, \dots, m$$

$$\sigma_{1\tilde{y}_{outik}} = \frac{1}{N} \sum_{t=0}^{N-1} [\tilde{y}_{outi}(k-t) - \mu_{\tilde{y}_{outik}}]^2 \quad (10)$$

$$\sigma_{2\tilde{y}_{outik}} = \frac{1}{N} \sum_{t=0}^{N-1} [\tilde{y}_{outi}(k-t) - \mu_{\tilde{y}_{outik}}]^2 \quad (11)$$

the fault detector are given ,

$$d_{ik} = \frac{\sigma_{1\tilde{y}_{outik}}^2}{\sigma_{\tilde{y}_{outi0}}^2} - \ln \frac{\sigma_{2\tilde{y}_{outik}}^2}{\sigma_{\tilde{y}_{outi0}}^2} - 1 \quad (12)$$

with the following decision-making,

$$d_{ik} \begin{cases} > h_0 \\ < h_1 \end{cases} \leq 2 \ln \frac{N p_0}{1 - p_0} \quad (13)$$

in formula (13),  $h_0$  denotes that system doesn't change,  $h_1$  denotes that system changes.  $p_0$  is the preengaged probability of no fault in whole system.

## 4 FAULT DIAGNOSIS

Suppose we detect that the system get fault at time  $k_1$ , then the follow method can be used to diagnose the fault in sensors. Because the main system has no fault, the output forecast serial  $\hat{y}(t)$  of main system, which get from formula, is correct. So the input of sensor is correct. Then we can give the parameter estimate input-output equation of sensor,

$$y_{out}(t) = \hat{h}(t) \hat{y}(t) + \hat{b}(t) \quad (14)$$

The fault estimate algorithm are given by following:

(1) Filter equation

From formula (4) we can see there is noise  $W(t)$  in  $y_{out}(t)$ , so there are noise in the series of  $\{y(t)\}$ . Accordingly, there are noise in the estimate value  $\hat{y}(t)$  in formula (5).

The filter equation of fault diagnosis from time  $k1 + m$  is given

$$\begin{cases} \bar{y}_{out}(t) = \frac{1}{t} \sum_{j=k1}^{k1+t-1} y_{out}(j) \\ \bar{\hat{y}}(t) = \frac{1}{t} \sum_{j=k1}^{k1+t-1} \hat{y}(j) \end{cases} \\ t = m, m+1 \dots m+l-1 \quad (15)$$

(2) Fitting equation

$l$  step fitting equation is given,

$$\bar{y}_{out}(t) = \hat{h}_m \bar{\hat{y}}(t) + \hat{b}_m \\ t = m, m+1 \dots m+l-1 \quad (16)$$

(3) Least-square

Using least-square method solve the  $l$  step fitting equation (16), we can obtain the results

$$\hat{h}_{il} = \left[ \sum_{j=m}^{m+l-1} \bar{y}_{outi}(j) \bar{\hat{y}}_i(j) - \frac{1}{l} \sum_{j=m}^{m+l-1} \bar{\hat{y}}_i(j) \cdot \sum_{j=m}^{m+l-1} \bar{y}_{outi}(j) \right] \\ \div \left[ \sum_{j=m}^{m+l-1} \bar{\hat{y}}_i(j)^2 - \frac{1}{l} \left[ \sum_{j=m}^{m+l-1} \bar{\hat{y}}_i(j) \right]^2 \right] \quad (17)$$

$$\hat{b}_{il} = \frac{1}{l} \left[ \sum_{j=m}^{m+l-1} \bar{y}_{outi}(j) - \sum_{j=m}^{m+l-1} \bar{\hat{y}}_i(j) \cdot \hat{h}_{im} \right] \quad (18)$$

(4) Convergence adjudicate

With formula (18) and (19), for an initial value  $l_1$ , estimate the parameter of sensor with step length  $q$ . If  $|\hat{h}_{il+q} - \hat{h}_{il}| \leq \varepsilon_1$  and  $|\hat{b}_{il+q} - \hat{b}_{il}| \leq \varepsilon_2$  for the given positive precision  $\varepsilon_1$  and  $\varepsilon_2$ , then  $\hat{h}_{il+q}, \hat{b}_{il+q}$  are the parameters of sensor with fault.

## 5 SIMULATION ANALYZING

The linear control system of multi-input and output is considered as below:

$$x(t+1) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t)$$

$$y_{out}(t) = ky(t) + b + W(t)$$

where

$$A = \begin{bmatrix} 0 & 1 \\ -0.5 & -1.5 \end{bmatrix}, B = \begin{bmatrix} 0.2 & 0.3 \\ 1 & 0.7 \end{bmatrix},$$

$$C = \begin{bmatrix} 1 & 0.2 \\ 0.3 & 0.5 \end{bmatrix}, D = 0$$

$$u(t) = \begin{bmatrix} 10 \sin 0.3t \\ 0.08t \end{bmatrix}, x(0) = 0$$

$$h = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, b = 0, W(t) \text{ is zero-average gauss noise}$$

The previous two hundred dots in the simulation are the normal area, the model of input and output is established based on  $u(t), y_{out}(t)$ . The plus fault of input to sensor one at dot 250  $h = 1.1$ . The intercept fault of input to sensor 2 at dot 300  $b = 1.0$ . The simulation results of fault are described as Fig. 2, Fig. 3, Fig. 4, Fig. 5:

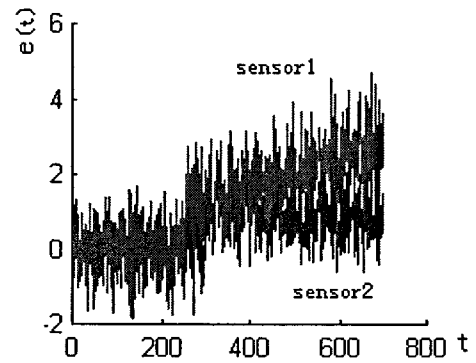


Fig. 2 sensors output error

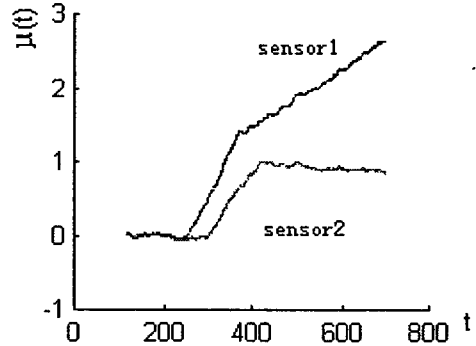


Fig. 3 sensors output error average

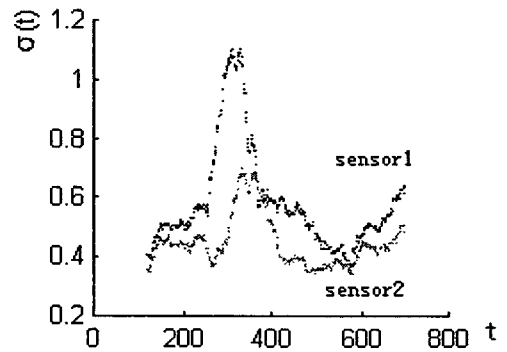


Fig. 4 sensors output square error

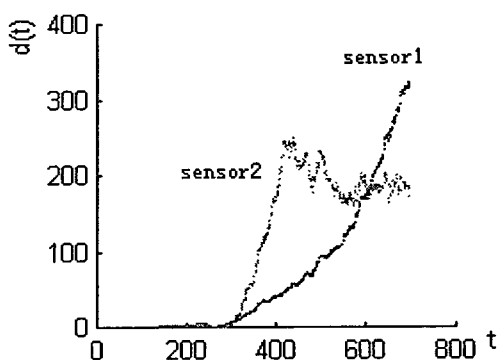


Fig.5 decision-making value for fault detection of sensors

The results of fault examined are described as below:

Table 1 the results of fault examined

| Sensors          | Sensor 1             |                      | Sensor 2             |                      |
|------------------|----------------------|----------------------|----------------------|----------------------|
|                  | <i>h</i>             | <i>b</i>             | <i>h</i>             | <i>b</i>             |
| Occurring time   | 250                  | —                    | —                    | 300                  |
| Detecting time   | 261                  | 261                  | 312                  | 312                  |
| Estimating time  | 361                  | 361                  | 492                  | 492                  |
| Actual value     | $h_1 = 1.1$          | $b_1 = 0$            | $h_2 = 1$            | $b_2 = 1$            |
| Estimating value | $\hat{h}_1 = 1.0995$ | $\hat{b}_1 = 0.0317$ | $\hat{h}_2 = 0.9927$ | $\hat{b}_2 = 1.0362$ |

## 6 CONCLUSION

The novel approach based on parameters estimation which is presented in this paper for fault detection and diagnosis in sensors is an simple and practical method. This method is merely on the basis of knowing the parameter of sensor model and the work system can be blackbox which can be built in parameter estimation method. Accordingly, the residual generator can be built.

From the results of simulation, we can see that beys decision-making theory for fault detection is fast and the least-square computative algorithm for fault diagnosis is

fast and accurate meanwhile have strong ability of wiping out noise. In addition, these methods can also be used in the fault detection and diagnosis for the executor of linear system.

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