Design and analysis of fault observer of MIMO system with systematic error and measurement error

Hua Xingxing\(^a\), Huang Darong\(^b\) and Bo Mi\(^b\)

\(^a\)College of Mathematical and Statistics, Chongqing Jiaotong University, Chongqing, People’s Republic of China; \(^b\)College of Information Science and Engineering, Chongqing Jiaotong University, Chongqing, People’s Republic of China

**ABSTRACT**

A fault observer of the MIMO (multiple input multiple output) feedback fault system with measurement error and system error is designed and analysed based on the linear time-invariant system. First, the disturbance system with system error and measurement error in the case of failure is given. Second, the expression form of system error is obtained, and the system error is divided into the random error part and the error part generated by the system error at the last moment. Then, a fault diagnosis observer is given for a fault system with both system error and measurement error. Finally, simulation results are presented to show the effectiveness of the proposed method.

1. Introduction

With the rapid development of science and technology, the complexity of modern industrial control is increasing consistently. Accordingly, the possibility of system failure has become higher and higher. Therefore, the fault diagnosis of industrial systems has become a very active area of research because of the security and reliability of the whole system (Lin & Antsaklis, 2009; Zhou, Liu, & He, 2013; Zhou, Shi, & He, 2014). In practice engineering, the fault diagnosis technology has been widely used in safety maintenance of some complex systems such as aerospace system, industrial system and other practical systems (Deng, Shi, Zhu, Yu, & Zhu, 2017; Yang, Ding, & Li, 2015; Yang, Jiang, & Zhou D, 2017). So, how to design a kind of fault diagnosis mode is an important problem for detecting the running state of systems.

Over the last 40 years, all kinds of different fault diagnosis methods have been proposed. For example, some researchers pointed that the fault diagnosis may be implemented based on direct measurable signal (Yin, Xiao, Ding S, & Zhou, 2016). For this reason, the scholar has constructed and established all kinds of fault diagnosis model and algorithm based on neural network, fuzzy logic, expert system and so on (Zhou & Hu, 2009). In general, these methods and algorithms may achieve designed performances of objective systems. But in fact, in most practical industrial processes control systems are complicated multiple input and output systems (MIMO). So, how to set and design fault observer of MIMO has attracted attention (Lu, Meng, Jiang, & Zhao, 2016; Raimondo, Marseglia, Braatz, & Scott, 2016). The research results showed that the advantage of setting and designed fault observer of MIMO is that they may constantly monitor the running state of the whole system and acquire the fault information (Cai, Ferdowsi, & Sarangapani, 2016; Chen, Xu, Yan, Ding, & Zhou, 2015; Yang & Wang, 2015). And then these models were presented for the linear process. As we all know, because the industrial systems are nonlinear in practical application, the existing algorithm cannot meet the demand of application. Thus some new design idea has been proposed to solve the stable of systems. For example, Liang et al. have deduced the stability condition of limit zero of the MIMO system with discrete time (Liang, Mitsuaki, & Shi, 2007). Wang et al. have designed a fault-tolerant controller for a class of nonlinear MIMO discrete-time systems based online reinforcement learning algorithm (Wang, Liu, Zhang, & Xiao, 2016). The fault-tolerant control strategy may meet the performance of discrete-time systems. Meanwhile, a novel observer-based output feedback fault-tolerant controller has been constructed (Zhang & Jiang, 2010). The controller is adaptive.

And unfortunately, the control performance of the systems is usually affected by the accuracy of the monitor tool and equipment. In fact, by proving experimentation, the errors are inevitable in all the stationary and dynamic measuring process which prevents us to get the real value of the measured quantity directly. Obviously, the
control performance of the system is influenced by the measurement error. To overcome the problem, the invariant and immeasurable subspace is introduced to solve Beard fault detection filter (BFDF) (Massoumnia, 1986). Moreover, considering with external disturbances and uncertainties of systems, a fault detection actuator based on interval observer has been designed to ensure that the fault-tolerant actuator’ performance is influenced by the bounded condition (Guo & Zhu, 2016). They pointed out that the initial state of the MIMO system must lie within a narrow range. To overcome the shortage, a reduced order observer has been designed by singular value decomposition without considering the internal and external distractions (Lungu & Lungu, 2013). In addition, some researchers have presented that the bounded condition (Guo & Zhu, 2016). They pointed out the fault-free actuator’s performance is influenced by the uncertainties of systems, a fault detection actuator based on interval observer has been designed to ensure that the fault observer of the MIMO system can be obtained. Finally, the simulation results verified the effectiveness and reasonability of the presented model.

As proven by experiments, the statistic character of the system noise and the observation noise cannot be estimated or determined accurately during the measurement. So, most MIMO systems are with system error and measurement error. For simplicity, the whole system with system error and measurement error can be defined and described by the following equation:

\[
\dot{x}(t) = (A + \Delta A)x(t) + (B + \Delta B)u(t) + Ff(t) + Dw(t), t \geq t_0,
\]

\[
y(t) = (C + \Delta C)x(t),
\]

where \( f(t) \in \mathbb{R}^m \) is the fault, \( F \) is the fault vector, \( w(t) \in \mathbb{R}^p \) is the measurement error, \( D \) is the measurement error matrix with proper dimension, \( \Delta A, \Delta B, \Delta C \) describe the state system error, input system error and output system error, correspondingly. Without loss of generality, suppose that the measurement error meets the Lipschitz condition, i.e.

\[
||w(x_1(t)) - w(x_2(t))|| \leq ||x_1(t) - x_2(t)||.
\]

### 2. Model building

#### 2.1. Representation of the MIMO system with measurement error and system error

As we all know, the running state of the MIMO system is changed with time. Thus if the fault doesn’t happen, the equivalent systems of equations may be described as follows:

\[
\dot{x}(t) = Ax(t) + Bu(t), t \geq t_0,
\]

\[
y(t) = Cx(t),
\]

where \( x(t) \in \mathbb{R}^n \), \( y(t) \in \mathbb{R}^l \), \( u(t) \in \mathbb{R}^p \) are the system state, system output, fault-free input; \( A \in \mathbb{R}^{n \times n} \) is the fault-free system matrix, \( B \in \mathbb{R}^{n \times p} \) is the input matrix, \( C \in \mathbb{R}^{l \times n} \) is the output matrix.

In general, for a linear time-invariant multiple input multiple output (MIMO) feedback system, the input control function (3) as follows:

\[
u(t) = \tilde{C}[v(t) - G_2\xi(t) - y(t)],
\]

where \( v(t) \) is a reference input, \( \tilde{C} \) is the inverse Laplace transform matrix of the transfer function of the compensator, \( \xi(t) \) is the system output disturbance, \( G_2 \) is the disturbance matrix with the appropriate dimension.

Thus if we don’t consider the measurement error and system error, formula (1) may be rewritten through input control function (3) as follows:

\[
\dot{x}(t) = (A - B\tilde{C}C)x(t) + B\tilde{C}v(t) - B\tilde{C}G_2\xi(t),
\]

\[
y(t) = Cx(t). \tag{4}
\]

Obviously, by taking into various error sources, formula (2) may be rewritten by input control function (3) as follows:

\[
\dot{x}(t) = [(A + \Delta A) - (B + \Delta B)\tilde{C}(C + \Delta C)]x(t) + (B + \Delta B)\tilde{C}v(t) + Dw(t) - (B + \Delta B)\tilde{C}G_2\xi(t) + Ff(t),
\]

\[
y(t) = (C + \Delta C)x(t). \tag{5}
\]
systematic errors in the last moment and the other part is composed by the random errors of the whole system in the current moment. To analyse error-related issues, a corollary was introduced.

**Corollary 1:** If the matrixes of systematic errors meet the following limits:

\[
\Delta A_t = a \Delta A_{t-1} + b \varepsilon_t, t \geq 0, \tag{6}
\]

\[
\Delta B_t = a \Delta B_{t-1} + b \eta_t, t \geq 0, \tag{7}
\]

\[
\Delta C_t = a \Delta C_{t-1} + b \rho_t, t \geq 0, \tag{8}
\]

where \( \Delta A_t, \Delta B_t, \Delta C_t \) are system errors matrix in the current time, and \( \Delta A_{t-1}, \Delta B_{t-1}, \Delta C_{t-1} \) are system errors in the last moment; \( a \) and \( b \) were weight coefficient and satisfied: \( a + b = 1, a > 0 \) and \( b > 0 \). \( \varepsilon_t, \eta_t \) and \( \rho_t \) are random errors in the current time. And the random errors follow normal distribution hypothesis, i.e.

\[
\varepsilon_t \sim N(0, \sigma_{\varepsilon_t}^2), \; \eta_t \sim N(0, \sigma_{\eta_t}^2), \; \rho_t \sim N(0, \sigma_{\rho_t}^2).
\]

Thus the systematic matrixes in the current time are changed with the systematic error at initial stage and the random error at each stage.

**Proof:** According to the characters of the actual systems, formula (6) can be rewritten as follows:

\[
\Delta A_t = a \Delta A_{t-1} + b \varepsilon_t = a^2 \Delta A_{t-2} + ab \varepsilon_{t-1} + b \varepsilon_t = \cdots = a^t \Delta A_0 + b \sum_{i=0}^{t-1} a^i \varepsilon_{t-i}. \tag{9}
\]

Similarly, the following results may also be gotten.

\[
\Delta B_t = a^t \Delta B_0 + b \sum_{i=0}^{t-1} a^i \eta_{t-i}, \tag{10}
\]

\[
\Delta C_t = a^t \Delta C_0 + b \sum_{i=0}^{t-1} a^i \rho_{t-i}. \tag{11}
\]

Hence, the conclusion is true.

**Remark 1:**

1. If \( \Delta A_0 \) is a geometric sequence and it can be described as \( \Delta A_0 = b \varepsilon_0 \), formula (9) may be simplified as the following formula:

\[
\Delta A_t = b \sum_{i=0}^{t-1} a^i \varepsilon_{t-i}. \tag{12}
\]

2. If \( \Delta B_0 \) is a geometric sequence and it can be described as \( \Delta B_0 = b \eta_0 \), formula (11) may be simplified such as

\[
\Delta B_t = b \sum_{i=0}^{t-1} a^i \eta_{t-i}. \tag{13}
\]

3. If \( \Delta C_0 \) is a geometric sequence and it can be described as \( \Delta C_0 = b \rho_0 \), formula (12) may be simplified as follows:

\[
\Delta C_t = b \sum_{i=0}^{t-1} a^i \rho_{t-i}. \tag{14}
\]

To detect accurately the running performance of the system with the systematic errors, the fault diagnosis observer needs to be designed combining with the form of system errors described in the whole system (5) in the next section.

### 3. Design and analysis of fault diagnosis observer

Moreover, to design the reasonable fault observer, system (5) may be rewritten as follows:

\[
\dot{x}(t) = [(A + \Delta A_t) - (B + \Delta B_t)\hat{C}(C + \Delta C_t)]x(t) \\
+ (B + \Delta B_t)\hat{C}v(t) + Dw(t) \\
- (B + \Delta B_t)\hat{C}2\xi(t) + Ff(t) \\
y(t) = (C + \Delta C_t)x(t). \tag{15}
\]

According to the system in formula (15), the fault diagnosis observer may be designed as follows:

\[
\dot{\hat{x}}(t) = (A - \hat{B}\hat{C})\hat{x}(t) + \hat{B}\hat{C}v(t) + \hat{F}f(t) \\
+ D\hat{w}(t) + L[\hat{y}(t) - y(t)], \\
\hat{y}(t) = \hat{C}\hat{x}(t), \tag{16}
\]

where \( \hat{x}(t) \in R^n \) indicates the estimation value of the state vector; \( \hat{y}(t) \in R^n \) is the output vector of the observer; \( \hat{w}(t) \in R^n \) is the measurement error of the observer, \( L \) is the observer gain matrix.

For simplicity of analysis, the error estimation between the original state and estimation state may be established as follows:

\[
e_{x}(t) = x(t) - \hat{x}(t), \quad e_{\varepsilon}(t) = f(t) - \hat{f}(t),
\]

\[
e_{y}(t) = y(t) - \hat{y}(t), \quad e_{w}(t) = w(t) - \hat{w}(t).
\]

Notice that \( e_{x}(t) \) is the state error estimation, \( e_{\varepsilon}(t) \) is the fault error estimation, \( e_{y}(t) \) is the output error estimation and \( e_{w}(t) \) is the measurement error estimation.
Then, by formulas (15) and (16), the error dynamic equation of the whole system may be rewritten and reconstructed as follows:

\[
\dot{e}_r(t) = (A - B\bar{C}C - LC)e_r(t) + (\Delta A_t - B\bar{C}\Delta C_t - \Delta B_t\bar{C}C - L\Delta C_t)x(t) - (B + \Delta B_t)\bar{C}G_2\xi(t) + D\bar{e}_f(t) + \Delta B_t\bar{C}v(t) + F\bar{e}_f(t),
\]

where the arbitrary scalar \(e > 0\) may be satisfied.

\[
e_r(t) = C_e\varepsilon_x(t) + \Delta C_ex(t).
\]

In our experiment system, the fault of the original system is almost a constant. Therefore, the derivate of the fault error \(e_r(t)\) may be rewritten as follows:

\[
\dot{e}_r(t) = -\dot{f}(t).
\]

To verify and get some conclusions of fault observer designed in this section, the lemma in Xiang, Su, and Chu (2006) was introduced to get the corresponding results. It is described as follows.

**Lemma 1:** For any appropriate dimension and certain vectors \(X\) and \(Y\), they satisfied the following condition:

\[
X^TY + Y^TX \leq \varepsilon X^TX + \varepsilon^{-1}Y^TY,
\]

where the arbitrary scalar \(\varepsilon\) meets \(\varepsilon > 0\).

The main results in this paper are shown as follows.

**Theorem 1:** For the arbitrary given scalars \(\gamma > 0\) and \(\varepsilon > 0\), if there exist a symmetrical positive definite matrix \(P \in R^{n \times n}\) and a matrix \(Q \in R^{1 \times q}\), when the following conditions may be satisfied.

\[
F^TP = QC, \quad \dot{f}(t) = \Gamma Qe_r(t).
\]

Thus to guarantee that the error system (17) has good robust stability, the following formula should to be meet:

\[
\begin{bmatrix}
Z_{11} + \varepsilon I_d & -P(B + \Delta B_t)\bar{C}G_2 & PD & C^T \\
* & -\gamma^2I_p & 0 & 0 \\
* & * & -\varepsilon I_d & 0 \\
* & * & * & -I_q
\end{bmatrix} < 0. \tag{20}
\]

Notice that \(\Gamma\) is an adaptive learning rate, and \(G = PL, Z_{11} = (A - B\bar{C}C - LC)^T P + (A - B\bar{C}C - LC)\).

**Proof:** To thoroughly verify the conclusion in Theorem 1, the following Lyapunov function was established.

\[
V(t) = e_r^T(t)P e_x(t) + e_r^T(t)\Gamma^{-1} e_r(t), \tag{21}
\]

where \(P\) is a symmetric positive definite matrix.

Let \(x(t) = 0, v(t) = 0\), the derivative of formula (21) is

\[
\dot{V}(t) = e_r^T(t)[(A - B\bar{C}C - LC)^T P + (A - B\bar{C}C - LC)] e_r(t) + 2e_r^T(t)PD\bar{e}_f(t) - 2e_r^T(t)P(B + \Delta B_t)\bar{C}G_2\xi(t) + 2e_r^T(t)P\bar{e}_f(t) - e_r^T(t)C^TP\bar{e}_f(t). \tag{22}
\]

By formula (19), Equation (22) can be rewritten as

\[
\dot{V}(t) = e_r^T(t)[(A - B\bar{C}C - LC)^T P + (A - B\bar{C}C - LC)] e_r(t) + 2e_r^T(t)PD\bar{e}_f(t) - 2e_r^T(t)P(B + \Delta B_t)\bar{C}G_2\xi(t). \tag{23}
\]

Furthermore, we have defined the energy function combing with the disturbance and output of systems, i.e.

\[
J = \int_0^T e_r^T(t)e_r(t) - \gamma^2\xi^T(t)\xi(t)dt. \tag{24}
\]

Moreover, applying Lemma 1, the following formula may be deduced through the skills of magnifying and shrinking of the equation,

\[
J \leq \int_0^T \phi^T(t)\Lambda\phi(t)dt, \tag{25}
\]

where

\[
\phi(t) = \begin{bmatrix} e_x(t) \\ \xi(t) \end{bmatrix},
\]

\[
\Lambda = \begin{bmatrix}
Z_{11} + C^T C + \varepsilon I_d & \varepsilon^{-1}PDD^T P - P(B + \Delta B_t)\bar{C}G_2 \\
* & -\gamma^2I_p
\end{bmatrix}. \tag{27}
\]

In formula (27), if \(\Lambda < 0\) holds, formula (20) may be obtained by Schur complement theorem. As a result, the state estimation error and the failure estimation error are stability and \(||e_r(t)||_2 < \gamma||\xi(t)||_2\).

So, the proof is ended.

### 4. Numerical verification

In this section, a numerical example is given to verify the rationality of fault diagnostic observer, which will demonstrate the advantages of the proposed algorithm in generic fault estimation.

Consider the system (17), the fourth-order mode is demonstrated the advantages of the proposed algorithm in generic fault estimation.

**Proof:** To thoroughly verify the conclusion in Theorem 1, the following Lyapunov function was established.

\[
V(t) = e_r^T(t)P e_x(t) + e_r^T(t)\Gamma^{-1} e_r(t), \tag{21}
\]

where \(P\) is a symmetric positive definite matrix.
When the system errors and measurement errors exist simultaneously, the system error weight was supposed as $a = 0.7$ and $b = 0.3$. Meanwhile, the normal distribution of the random errors in the system error is subject to the mean 0.6 and the variance 0.01.

The Lipschitz nonlinear function $w(x(t))$ is added to show that the proposed methods indeed work for the systems which illustrated in the previous section. When $H_\infty$ performance indicator $\gamma = 3.0$, the arbitrary scalar was $\varepsilon = 2.145$ in Lemma 1, and the adaptive learning rate values are $\Gamma' = 25$, by using the method of LMI, $L$ and $Q$ which satisfy Equation (19) are obtained as

$$L = \begin{bmatrix} -0.063 & 3.3761 \\ -1.896 & -4.5616 \\ 0.2768 & 1.1299 \\ 1.9565 & 0.2118 \end{bmatrix}, \quad Q = \begin{bmatrix} 0.6758 & 0.5479 \end{bmatrix}.$$ 

According to the fault diagnosis observer design in this paper, taking the simulation step 0.01 s, those simulation diagrams are derived as follows.

To show the performance of the detection observer, we assume that the initial state of the system state values and its estimation values are defined as $x(0) = [1, -1, 1, -1]^T$, $\hat{x}(0) = [-1, 1, -1, 1]^T$ in the no-fault system. The observer error curve in system (17) with no-fault and under fault can be obtained in Figures 1 and 2, respectively.

In order to show the system performance better in the fault system, the initial state of the system state values and its estimation values can be described as the follows:

$$x(0) = [0.1, 0.1, 0.1, 0.1]^T, \quad \hat{x}(0) = [0.1, 0.1, 0.1, 0.1]^T.$$ 

Thus the error curve under fault conditions can be obtained as follows.

It can be seen that from Figures 1 and 2 the error dynamic equation as given in (17) is fast, tends to a stable state. The result indicated that the observer demonstrated in the second section is feasible and effective.
As shown in Figures 4–7, all the system state values estimation can track the real status values well.

5. Conclusion

The main contributions of this paper can be described in the following aspects. (i) Based on the nominal system, an MIMO feedback system with measurement error and system error is studied. Considering the system output disturbance, we can get the system that we want to an observer to detection. (ii) Based on the nominal system given in the second part, we have inferred the representation of the system error. (iii) According to the error dynamic equation, the effectiveness of the proposed method is verified through simulation experiments.

In comparison with existing observer system, this system includes system errors and measurement errors, so the performance and the dynamic of the system can be described more precisely. From here, the system we considered in this paper may be more suitable for the actual engineering.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by National Natural Science Foundation of China: [Grant Numbers 61703063, 61663008, 61573076 and 61004118]; the Program for Excellent Talents of Chongqing Higher School of China P. R.: [Grant Number 2014-18]; the Science and Technology Research Project of Chongqing Municipal Education Commission of China P. R.: [Grant Numbers KJ1705121, KJ1705139 and KJZD-K201800701]; the Program of Chongqing Innovation and Entrepreneurship for Returned Overseas Scholars of China P. R.: [Grant Number cx2018110.]; the Scientific Research Foundation for the Returned Overseas Chinese Scholars: [Grant Number 2015-49].

ORCID

Huang Darong http://orcid.org/0000-0002-5068-5162

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