Fault Detection of Areo-engine Actuator Based on Adaptive Radial Basic Function Observer

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Abstract. Aiming at the fault detection problem of aero-engine actuators, a fault diagnosis method for aero-engine actuators based on adaptive RBF network observer is proposed. Firstly, the system model is established for the faulty actuator, and then the observer-based actuator fault diagnosis principle is established. Secondly, for the problem that the traditional observer is not sensitive to the gradual fault, the nonlinear approximation characteristics of the RBF network are used. The adaptive fault observer design method based on RBF network is applied. At the same time, the sufficient conditions for the convergence of the observer error system are given by using the Lyapunov stability analysis method. Finally, the simulation experiments of different types of actuators for a turbofan engine are carried out. The results show that the adaptive RBF observer designed in this paper is more effective in detecting faults and has certain fault estimation ability.

1. Introduction

The aero-engine control system has gradually developed from the early mechanical hydraulic control to the present FADEC and distributed control system[1], but the structure of the control system has become increasingly complex, which directly increases the possibility of engine component failure, and the reliability of the system becomes more prominent. It has been found that engine control system faults account for a large proportion of flight faults and often led to catastrophic accidents in flight. As an important part of the aero-engine control system, the actuator plays a vital role in executing the instructions issued by the controller and adjusting the engine condition in time. However, it is a component with low reliability and high failure rate in the system. Therefore, it is of great significance to monitor the condition of the actuator in real time and detect fault components timely and accurately, so as to provide a reliable condition for active fault-tolerant control and ensure the safety of the control system [2-4].

At present, domestic scholars have carried out many fruitful new researches on fault detection of actuator of aero-engine. For example, literature [5] and [6] have established on-line fault detection methods based on observer and kalman filter, and achieved good detection results. In order to improve the robustness to noise interference and model parameter changes in the process of aero-engine diagnosis, a detection method based on UIO observer was established in literature [7]. Compared with Kalman filtering algorithm, UIO diagnosis method is more robust to detect and isolate actuator faults. Due to its good adaptability and function approximation ability, RBF network has been widely used in the fields of pattern recognition and nonlinear control, etc. Some researchers have used the learning ability of RBF network to design an adaptive fault diagnosis observer, and obtained some research achievements in online fault estimation.
Aiming at aircraft actuator fault detection problems, actuator failure model is established, and researching the general design method of fault detection observer. On the basis of the analysis the characteristic of RBF network, an adaptive fault diagnosis observer based on RBF network is designed. By using two kinds of observer to detect different fault types of engine actuator, and the simulation results are analyzed and summarized.

2. Mathematical Model of Actuator Fault
Actuator faults refer to the difference between the input command of the actuator and the actual output, resulting in the loss of all or part of the control function [10]. Consider the nonlinear dynamic system with the following actuator failure:

\[
\dot{x}(t) = Ax(t) + Bu(t) + f(x) + Ef_a(t) + \varphi(t)
\]

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

Where, \( x(t) \in \mathbb{R}^n \) is the condition vector, \( u(t) \in \mathbb{R}^m \) is the control vector, and \( y(t) \in \mathbb{R}^p \) is the output vector. \( A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, C \in \mathbb{R}^{m \times n} \) is the condition, input and output coefficient matrix of the system respectively, \( f(x) \in \mathbb{R}^n \) is the smooth function, representing the nonlinearity of the system, \( \varphi(t) \in \mathbb{R}^{\text{out}} \) represents the modeling error and disturbance term of the system. \( E \in \mathbb{R}^{\text{out} \times n} \) is the fault distribution matrix, \( f_a(x) \in \mathbb{R}^{\text{out}} \) is the fault function. And following assumptions are made:

- system \((A, C)\) is observable, and nonlinear \( f(x) \) satisfies Lipschitz condition, that is \( k > 0 \), so that \( \|f(x_1) - f(x_2)\| \leq k\|x_1 - x_2\| \) is true;
- the interference and error terms of the system are bounded in the definition domain, that is \( |\varphi(t)| < \alpha \).

3. Fault Detection Observer Design
According to the nonlinear system model, a fault detection observer is introduced for the system without fault as follows:

\[
\dot{\hat{x}}(t) = A\hat{x}(t) + \tilde{f}(\hat{x}(t)) + Bu(t) + D(y(t) - \hat{y}(t))
\]

\[
\hat{y}(t) = C\hat{x}(t)
\]

Where, \( \hat{x}(t) \in \mathbb{R}^n \) is the condition vector of the observer, \( \hat{y}(t) \in \mathbb{R}^p \) is the observer output vector, and \( D \in \mathbb{R}^{p \times n} \) is the observer gain matrix. Condition error \( \gamma(t) \overset{\text{def}}{=} x(t) - \hat{x}(t) \) and output residual \( e(t) \overset{\text{def}}{=} y(t) - \hat{y}(t) \) are defined. The error equation can be obtained from system equation (1) and fault detection observer equation (2) as follows:

\[
\dot{\gamma}(t) = (A - L)\gamma(t) + \tilde{f}(x(t)) - \tilde{f}(\hat{x}(t)) + Ef_a(t)
\]

\[
e(t) = Cy(t)
\]

The mission of the detection observer is to design the feedback gain array \( D \) so that the same filter can diagnose as many faults as possible and different faults have different directions in the output residuals. There is the following theorem: if there is a symmetric positive definite matrix \( S > 0 \), \( T > 0 \) and matrix \( D \), the following inequality is true:

\[
(A - DC)^T S + S(A - DC) + k^2 + S^2 < -T
\]

Then, there is a fault detection observer in equation (1), which is equation (2), so that the condition error equation (3) is uniformly and ultimately bounded when there is no fault.

According to theorem 1, when the actuator is well working, the condition estimation error \( \gamma(t) \) should be a bounded value, and when the system fails, the fault detection observer is no longer stable, and the residual output will deviate from the bounded value when the system fails. The threshold value is used for fault judgment and detection. When \( \|\gamma(t)\| < \lambda \), the condition of the actuator is well working. When \( \|\gamma(t)\| \geq \lambda \), the actuator fails.
4. Adaptive RBF Network Observer Design

4.1. Radial Basis Function (RBF) Network

Radial Basis Function (RBF) network is a three-layer feedforward neural network structure composed of input layer, hidden layer and output layer. The typical RBF neural network structure is shown in figure 1.

![Figure 1. Typical RBF neural network structure](image)

The prototype function of the radial basis network transfer function:

\[ \text{radbas}(n) = e^{-\|x\|^2} \]  

According to literature [12], there are the following theorems:

**Theorem 1:** let \( f(x) \) be a continuous function defined on set \( \Omega \). For any \( \varepsilon > 0 \), RBF network \( \hat{f}(x) \) and optimal weight \( \theta \) exist, so that:

\[ \sup_{\Omega} \| f(x) - \hat{f}(x) \| \leq \varepsilon \quad x \in \Omega \]  

Where, \( \varepsilon \) is the network approximation error, and \( \varepsilon \) is assumed to be small enough to ignore its influence.

System actuator fault \( s \) can be described by the following RBF network:

\[ f_s(t) = \theta(t) r(\hat{x}) = \sum_{i=1}^{n} \theta_i r_i(\hat{x}(t)) \]  

Where, \( n \) is the number of hidden layer elements, \( \theta(t) \in \mathbb{R}^{n \times n} \) is the network optimal weight matrix, \( r_i(\hat{x}(t)) \) is the output of the \( i \)th hidden layer element, and the activation function of hidden layer element adopts gaussian function. Assuming that the optimal weight of RBF network with actuator failure is constant or slow variable, \( d\theta(t)/dt = 0 \) can be approximated.

4.2. Adaptive RBF Observer Design

According to the characteristics of RBF network, the adaptive fault diagnosis observer is constructed as follows:

\[ \dot{\hat{x}}(t) = A\hat{x}(t) + \bar{f}(\hat{x}(t)) + Bu(t) + E\dot{\hat{\theta}}(t) r(\hat{x}(t)) + D(y(t) - \tilde{y}(t)) \]

\[ \tilde{y}(t) = C\hat{x}(t) \]  

Where, \( \dot{\hat{x}}(t) \in \mathbb{R}^n \) is the condition vector of the observer, \( \dot{\hat{\theta}}(t) \in \mathbb{R}^{n \times n} \) is the estimation of the weight matrix, and its initial value is \( \dot{\hat{\theta}}(t) = 0^{n \times n} \). Define fault estimate error \( \tilde{\theta}(t) \equiv \theta(t) - \dot{\hat{\theta}}(t) \).

The condition error equation after failure is:

\[ \dot{\tilde{y}}(t) = (A - DC)\tilde{y}(t) + \bar{f}(\hat{x}(t)) - \bar{\hat{f}}(\hat{x}(t)) + B\tilde{\theta}(t) r(\hat{x}(t)) \]  

An adaptive fault observer is designed so that:

\[ \lim_{t \to \infty} \tilde{y}(t) = 0 \quad \text{and} \quad \lim_{t \to \infty} \tilde{\theta}(t) = 0 \]

According to the error equation (9) and reference [13], the following lemma is given:

**Lemma 1:** if symmetry exists in positive definite matrices \( S > 0 \), \( T > 0 \) and \( D \in \mathbb{R}^{n \times n} \), \( F \in \mathbb{R}^{n \times n} \) satisfies the following conditions:

\[ (A - DC)^T S + S(A - DC) + k^2 + S^2 = -T \]

\[ FC = E^T S \]
And the adaptive law of fault parameter estimation is:

$$
\dot{\hat{\theta}}(t) = \begin{bmatrix}
-\Sigma \hat{\theta}(t) + \Gamma F \varepsilon(t) \hat{x}^T(t) \\
\Gamma F \varepsilon(t) \hat{x}^T(t)
\end{bmatrix}
$$

(12)

Where, \( \varepsilon(t), \hat{\theta}(t) \) ∈ \( \Omega_e \) and parametric matrices \( \Sigma \) and \( \Gamma \) are symmetric positive definite matrices. There is an adaptive fault diagnosis observer, which makes \( \varepsilon(t), \hat{\theta}(t) \) converge to \( \Omega_e \).

$$
\delta_0 = \min \left\{ \frac{\rho_0}{2\rho_3}, \frac{\rho_1}{\rho_4} \right\}
$$

$$
\Omega_e = \left\{ \varepsilon(t), \hat{\theta}(t) \right\} \frac{\rho_{\max}(S)}{\| C \|^2} \| \varepsilon(t) \|^2 + \frac{\rho_2}{2} \| \hat{\theta}(t) \|^2
$$

$$
\hat{\Omega}_e = \left\{ \varepsilon(t), \hat{\theta}(t) \right\} \frac{\rho_{\max}(S)}{\| C \|^2} \| \varepsilon(t) \|^2 + \frac{\rho_2}{2} \| \hat{\theta}(t) \|^2
$$

$$
> \rho_3 \sigma_0^2 + \frac{1}{\delta_0} \left[ \left( \rho_0 \| T^{-1} S \|^2 + \rho_2 \right) \alpha^2 + \rho_2 \sigma_0^2 \right]

$$

$$
\leq \rho_0 \sigma_0^2 + \frac{1}{\delta_0} \left[ \left( \rho_0 \| T^{-1} S \|^2 + \rho_2 \right) \alpha^2 + \rho_2 \sigma_0^2 \right]
$$

Parameters are defined as follows:

$$
\rho_0 = \rho_{\max}(T); \rho_1 = \rho_{\max}(\Sigma \Gamma^{-1}); \rho_2 = \rho_{\max}(\Sigma \Gamma^{-1}); \rho_3 = \rho_{\max}(\Gamma^{-1});
\rho_4 = \rho_{\max}(\Gamma^{-1}); \rho_5 = \rho_{\max}(S); \rho_6 = \rho_{\max}(ST^{-1}S); \sigma_0 = \sup \| \hat{\theta}(t) \|
$$

(13)

5. Simulation Experiment

Taking the linear model of a turbofan engine under the condition of \( H=5 \text{km} \) and \( M_a=0.5 \) as an example, the sampling period \( T=0.01 \text{s} \), and the fault diagnosis of the engine actuator is simulated. Selection can comprehensively reflect the aerodynamic heat and work condition of the engine compressor speed \( n_H \), fan speed \( n_c \) as condition variables, selection of main chamber oil \( W_f \), nozzle cross-sectional area \( A_k \), fan guide vane angle \( \alpha \), and adjustable stator blade Angle of compressor \( \alpha_c \) as the control vector, selection of high pressure compressor rotate speed \( n_H \), fan speed \( n_c \), compressor outlet pressure \( P_s \), low pressure turbine outlet temperature \( T_k \), low pressure turbine outlet pressure \( P_s \), turbine pressure reduction ratio \( \pi \) as the output vector.

Firstly, the nonlinear degree \( a \) of the actuator can be expressed as:

$$
\dot{f}(x) = \Delta A x(t) + \omega(t)
$$

Where, \( \Delta A = 0.1 \sin(t) \) \( \mathbf{I}_{n \times n} \) is a diagonal matrix of order \( n \) and \( \omega(t) \) is gaussian white noise.

According to modeling requirements, the nonlinear dynamic equation of the system can be written as follows:

$$
\dot{x}(t) = (A + \Delta A)x(t) + Bu(t) + Ef_u(t) + \omega(t)
$$

$$
y(t) = Cx(t)
$$

(14)

Where, \( f_u(t) \) satisfies the model function of actuator fault, and the parameters of the nonlinear dynamic equation of the system are:

$$
A = \begin{bmatrix}
-1.9327 & 0.86475 \\
1.41240 & -2.4503
\end{bmatrix}
$$

$$
\Delta A = \begin{bmatrix}
0.1 \sin(t) & 0 \\
0 & 0.1 \sin(t)
\end{bmatrix}
$$

$$
E = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
$$
In the simulation experiment, three fault types were set up respectively: the constant deviation fault of the fuel nozzle in the main combustion chamber, the gradual failure of the fan inlet guide vane regulating mechanism, and the failure of the nozzle motor mechanism.

5.1. Implementation and simulation of common fault observer

Based on the nonlinear dynamic model equation of actuator established above, according to the design method in section 3, the fault detection observer is designed as follows:

$$\dot{x}(t) = (A + \Delta A)x(t) + Bu(t) + D(y(t) - \hat{y}(t)) + \omega(t)$$

where

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Firstly, it is assumed that the fuel flow of the fuel nozzle of the main combustion chamber deviates by -3% when t=10s. This fault is a type of constant deviation fault. The dimensionless amplitude change curve of the estimated residual error of the engine output is obtained through simulation, as shown in FIG. 2 (Where, $e(\Delta n_H)$ and $e(\Delta n_L)$ are the relative increment of the difference between the actual high and low pressure rotor speed of the engine and the standard speed under the simplified steady-condition model). It can be seen from the figure that, in the absence of failure, the observer can realize the condition estimation of the actuator. Due to the influence of noise, the output residual amplitude of the engine fluctuates around 5. After failure occurs, high pressure rotor speed and low pressure rotor speed estimation residual began to rapidly increase and reached the basic stability after a certain time, residual amplitude fluctuations within 20 to 25, shows that fault detection observer can quickly detect the constant deviation of the actuator failures, but under the noise interference, the residual value is not stable, and the big fluctuation.

![Figure 2](image1)

Figure 2. When \( w_f \) has a constant deviation fault, the fault detection observer residual output in \( \Delta n_H \), \( \Delta n_L \).

Similarly, when t=10s, it is assumed that a gradual failure occurs in the angle adjustment mechanism of fan inlet guide blade, and the fault expression is, and the simulation results are shown in Figure 3. It can be seen from the figure that, at 10s, the fault was introduced into the system, and the estimated residual error of the high pressure rotor speed and low pressure rotor speed began to increase slowly with the
extension of the fault time, indicating that the fault detection observer could detect the gradual fault of the actuator, but it can be seen from the figure, for the gradual failure of the actuator, the observer has slow response and low sensitivity to the failure, the condition of the actuator can only be clarified after a period of time of failure, and the detection effect is poor.

Figure 3. When $\alpha_f$ has a gradual fault, the fault detection observer residual output in $\Delta n_H$, $\Delta n_L$.

By the same method, when $t=10s$, the engine nozzle actuator stuck, and the simulation results are shown in Figure 4. It can be seen from the figure that after the nozzle actuator becomes stuck, the estimated residual error of high pressure rotor speed and low pressure rotor speed starts to increase rapidly and increases with the extension of the fault time, which indicates that the failure detection observer can quickly detect the stuck failure of the actuator.

Figure 4. When $\lambda_i$ has a actuator stuck fault, the fault detection observer residual output in $\Delta n_H$, $\Delta n_L$.

5.2. implementation and simulation of observer based on adaptive RBF network

According to the adaptive RBF network observer, the following fault detection observer is designed:

$$\dot{x}(t) = (A + \Delta A)\dot{x}(t) + B\bar{u}(t) + E\dot{\theta}(t)r(\dot{x}(t)) + D(\bar{y}(t) - \hat{\bar{y}}(t)) + w(t)$$

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

(16)

where

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

The same as the fault settings in section 4.1, the adaptive fault diagnosis observer based on RBF network is adopted for simulation analysis. In the figure, the solid line represents the actual fault and the dotted line represents the fault estimation. According to Figure 5, Figure 6 and Figure 7, the estimated
curve of $\theta$ almost coincides with the actual fault, indicating that the algorithm can well track the set fault trajectory.

After the failure of the actuator occurs, the residual error can be rapidly changed accordingly, so the actuator fault can be effectively detected and the size of the actuator fault can be estimated. Through comparative analysis of Figure 2 and Figure 5, it can be found that when the constant deviation fault occurs in the system actuator, the fault sensitivity of the two observers is basically the same, but in the stable condition, the residual error of the detection method based on RBF observer fluctuates less and is closer to the real value. According to the comparative analysis of Figure 3 and Figure 6, it can be found that the gradual failure of the system actuator occurs at 10s, and the output residual value of the observer is about 18 after the failure of the observer for 30s. The output residual value of the observer based on RBF network can reach 30 after 5s. Through the comparative analysis of Figure 4 and Figure 7, it can be found that the detection speed of the two observers is basically the same for the stuck fault.

Figure 5. When $w_f$ has a constant deviation fault, Adaptive fault observer residual output in $\Delta n_H, \Delta n_L$.

Figure 6. When $a_p$ has a gradual fault, Adaptive fault observer residual output in $\Delta n_H, \Delta n_L$. 
when $A_e$ has an actuator stuck fault, adaptive fault observer residual output in $\Delta n_H, \Delta n_L$.

6. Conclusion

This paper focuses on nonlinear engine control system, the problem of fault detection of aero-engine actuator using adaptive RBF network observer is studied. Through simulation, it can be found that, compared with the fault detection method based on ordinary observer, this method has a stronger ability to suppress noise, especially a higher sensitivity to gradual faults. Meanwhile, this method can well track the set fault trajectory, and has a certain ability to estimate the change trend of faults. Therefore, the fault detection method based on the adaptive RBF network observer has excellent fault detection ability and fault identification ability, which is of great practical value.

Acknowledgments

This work was partially supported by the National Natural Science Foundation of China(51506221), Shaanxi Science and Technology Plan Project(2015JQ5179).

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