Fault Diagnosis in a Hydraulic Position Servo System Using RBF Neural Network

LIU Hong-mei，WANG Shao-ping，OUYANG Ping-chao
(*School of Automation Science and Electrical Engineering, Beijing University of Aeronautics and Astronautics, Beijing 100083, China*)

Abstract: Considering the nonlinea r, time-varying and ripple coupling properties in the hydraulic servo system, a two-stage Radial Basis Function（RBF）neural network model is proposed to realize the failure detection and fault localization. The first-stage RBF neural network is adopted as a failure observer to realize the failure detection. The trained RBF observer, working concurrently with the actual system, accepts the input voltage signal to the servo valve and the measurements of the ram displacements, rebuilds the system states, and estimates accurately the output of the system. By comparing the estimated outputs with the actual measurements, the residual signal is generated and then analyzed to report the occurrence of faults. The second-stage RBF neural network can locate the fault occurring through the residual and net parameters of the first-stage RBF observer. Considering the slow convergence speed of the K-means clustering algorithm, an improved K-means clustering algorithm and a self-adaptive adjustment algorithm of learning rate are presented, which obtain the optimum learning rate by adjusting self-adaptive factor to guarantee the stability of the process and to quicken the convergence. The experimental results demonstrate that the two-stage RBF neural network model is effective in detecting and localizing the failure of the hydraulic position servo system.

Key words: failure diagnosis; hydraulic servo system; two-stage RBF neural network; improved K-means clustering algorithm

基于RBF神经网络的液压位置伺服系统故障诊断. 刘红梅，王少萍，欧阳平超. 中国航空学报(英文版),2006,19(4):346-353.

摘　要：针对液压系统的非线性、时变、流固耦合的特点，提出双级径向基函数（Radial Basis Function，RBF）神经网络模型实现液压伺服系统故障检测与定位。采用第 1 级 RBF 网络作为液压伺服系统的故障检测滤波器，通过实际系统与 RBF 观测器输出的残差实现液压伺服系统故障检测。利用第 1 级 RBF 观测器的输出残差和网络结构参数，应用第 2 级 RBF 网络实现液压伺服系统典型故障定位。针对 K 均值聚类算法收敛速度慢的缺点，提出了改进 K 均值聚类算法和学习速率自适应调整算法，利用网络优化结构参数和学习率，加快神经网络收敛速度，减少运算量。实验结果表明，利用双级 RBF 神经网络能够有效地检测出液压位置伺服系统的故障，并能实现系统的故障定位。

关键词：故障诊断；液压位置伺服系统；双级 RBF 神经网络；改进 K-均值聚类算法
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Due to the inherent nonlinearity existing in the hydraulic system, the failure mechanism become complex and the failure characteristics are difficult to extract. Model-based fault diagnosis method depends heavily on the accuracy of the mathematical model. An accuracy mathematical model of the process, however, is difficult to avail because of the nonlinearity and ripple coupling in actual hydraulic

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servo system. Therefore, Robustness of fault diagnosis method based on approximate linear model is worse[1].

Neural network has a strong nonlinear mapping ability and fault tolerance ability. It is easy for neural network to realize the nonlinear robust fault diagnosis[2]. Compared with BP neural network, Radial Basis Function (RBF) neural network has many advantages: faster convergence speed, less training iteration, stronger robustness and no local minimum…etc. In RBF neural network, the Gaussian function and the Least Square (LS) criterion are generally selected as the activation function of network and the objective function, respectively. Each node parameter of it can be adjusted iteratively by minimizing the LS criterion according to the gradient descent algorithm[2]. In addition, the RBF neural network observer can promptly approximate the control system model and precisely track the variation of model. So system faults can be detected according to the variation of neural network observer.

A failure observer based on RBF neural network can only distinguish the occurrence of faults, that is to say, RBF observer can only detect the residual error curve but can not localize the fault. In order to overcome this limitation, a combination of RBF observer and RBF localizer is proposed in this paper, the input of the RBF localizer is the residual between the RBF observer outputs and system outputs. The combinated RBF neural network can realize not only the fault detection, but also the fault localization in hydraulic servo system.

Fault observer based on RBF Neutral network has a strong self-adaptability. However, the stability of the algorithm is difficult to guarantee. Especially the K-means clustering algorithm requires determining the number of the hidden nodes beforehand, whose initial clustering centers will also heavily affect the convergence speed of network. Therefore, an improved the K-means clustering algorithm and self–adaptive adjustment algorithm of learning rate are presented in this paper, which obtain the optimum learning rate by adjusting the self-adaptive factor to guarantee the stability of the process, and adjust the connecting weights by the neural network self-adaptability. With the improved K-means clustering algorithm, the fault diagnosis system has enough self-adjustability and stability to realize the fault diagnosis in hydraulic servo system.

1 System Description

A schematic diagram of the hydraulic position servo system which is composed of a servo valve, an actuator, a displacement sensor and a load is shown in Fig.1, where x_f is the displacement of piston, F_L is the load, K_L is the load rigidity.

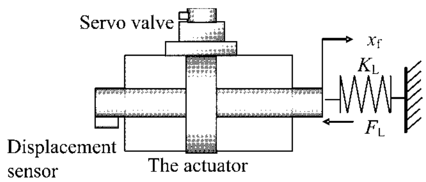

Fig.1 The hydraulic position servo system

In hydraulic servo system some possible faults are electric amplifier fault, servo valve fault, sensor fault, actuator fault…etc. The component faults affect not only the output of components, but also the output of the whole system. When faults occur, the parameters of the mathematical model will change. Consequently, the fault observer-based method can be used for the fault diagnosis in hydraulic servo system.

However, it is difficult to extract the failure characteristic because of the nonlinear characteristics, such as load fluid performance of servo valve, the friction in mechanism, the fluid compressibility, the pump pulsation and the coupling between oil supply system and servo system, which make the failure mechanism of hydraulic system complex.

RBF neural network has a strong nonlinear mapping ability and can approximate any nonlinear function. Consequently, a two-stage RBF network model is proposed to realize the fault detection and fault localization, as shown in Fig.2, in which the first-stage RBF neural serves as a failure observer, working concurrently with the actual system, accepts the input voltage signal to the servo valve and the measurements of the ram displacements, then rebuilds the system states. The output of the system is accurately estimated. By comparing the estimated output with the actual measurements, the residual signal is generated and then analyzed to report the occurrence of faults.

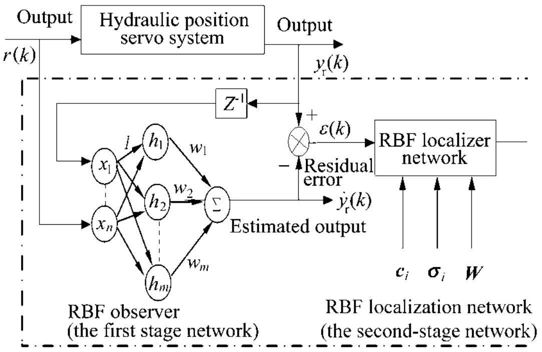

Fig.2　RBF neural network of the hydraulic servo system

The second-stage RBF neural network accepts the residual error signal and network parameters $\boldsymbol{\sigma}_i$, $\boldsymbol{c}_i$ and $\boldsymbol{W}$ of the first-stage RBF observer, and the fault localization and classification are realized according to the residual error and network parameters of the first-stage RBF observer.

2　Two-Stage RBF Neural Network Model

2.1　RBF fault observer

Suppose the hydraulic servo system can be described as

$$\left.\begin{aligned} \boldsymbol{X}(t) &= g(t, \boldsymbol{X}, \boldsymbol{U}, \boldsymbol{Y}, \boldsymbol{f}) \\ \boldsymbol{Y}(t) &= h(t, \boldsymbol{X}, \boldsymbol{U}, \boldsymbol{Y}, \boldsymbol{f}) \end{aligned}\right\} \qquad (1)$$

where $\boldsymbol{X}(t), \boldsymbol{Y}(t), \boldsymbol{U}(t)$ and $\boldsymbol{f}(t)$ stand for the status vector, the output vector, the control input vector and the failure vector respectively, g and h are the nonlinear vector functions.

Let the status observer be defined as

$$\left.\begin{aligned} \hat{\boldsymbol{X}}(t) &= g(t, \hat{\boldsymbol{X}}, \boldsymbol{U}, \boldsymbol{Y}, \hat{\boldsymbol{f}}) \\ \hat{\boldsymbol{Y}}(t) &= h(t, \hat{\boldsymbol{X}}, \boldsymbol{U}, \boldsymbol{Y}, \hat{\boldsymbol{f}}) \end{aligned}\right\} \qquad (2)$$

where $\hat{\boldsymbol{X}}(t), \hat{\boldsymbol{Y}}(t)$ and $\boldsymbol{f}(t)$ are estimated $\boldsymbol{X}(t), \boldsymbol{Y}(t)$ and $\boldsymbol{f}(t)$ respectively.

Define the status error to be

$$\boldsymbol{e}(t) = \boldsymbol{X}(t) - \hat{\boldsymbol{X}}(t) \qquad (3)$$

If $\boldsymbol{f}(t) = 0$ and $\boldsymbol{f}(t) \neq 0$, satisfy $\lim\limits_{t\to\infty} \boldsymbol{e}(t) = 0$, then Eq.(2) is called the fault observer of Eq.(1)[3].

In order to describe effectively the nonlinearity in the hydraulic servo system, the RBF neural network shown in Fig.2 is adopted as a fault observer, where y_r and r respectively stand for the output displacement of the ram and the input voltage signal to the servo valve and $\hat{y}_r$ is the estimated displacement of the fault observer.

The residual generation is based on comparison of actual and anticipated system response. The estimated system response is generated by a RBF neural network observer. The residual error is defined as the difference between actual and estimated output

$$\varepsilon(k) = y_f(k) - \hat{y}_f(k) \qquad (4)$$

Under normal operating conditions, the residual error is only due to unmodeled noise and disturbance and close to zero. But in the presence of some faults, the residual error deviates from zero in characteristic ways. The faults can be detected by the residual error.

2.2　RBF fault localizer

The RBF observer trained with the normal samples can exactly track the system model in normal condition, and the normal system model is distributedly memorized in the connecting weights. In the same way, the RBF observer trained with the fault samples memorized the fault system model in the connecting weights. In the different fault condition, the system model changes in the different way, and the weights of RBF observer will change in the same way. Consequently, the RBF observer parameters such as the connecting weights can be used for the fault diagnosis of hydraulic servo system.

The RBF observer trained with the normal samples has an ability of exactly tracking the system model in the normal condition. The difference between the estimated out of RBF observer and actual output of system is close to zero, and the difference is also called the residual error. But in the presence of faults, the difference will deviate from zero. Therefore, the faults could be detected by the residual error.

In brief, the faults in hydraulic servo system can be localized according to the residual and the structure parameters of the first-stage RBF observer.

The first-stage RBF observer trained with the normal samples tracks the system model, when the residual exceeds the threshold, it is ascertained that faults occur. In order to ascertain the concrete fault location, train the RBF observer with fault samples again, at this time, the connecting weights memorized the fault model of system. When the fault mode is different, the distribution of connecting weights is different. Consequently the network parameters such as the weights of fault observer and the residual error of normal observer could be used for fault localization and fault classification.

The second-stage RBF network is adopted as fault localizer and fault classifier. The residual error of system and parameters $\boldsymbol{\sigma}_i$, $\boldsymbol{c}_i$ and $\boldsymbol{W}$ of the first-stage RBF observer trained in fault condition act as inputs. And the outputs are system states, including normal condition, electric amplifier fault, the actuator fault and servo valve fault.

In order to exactly localize the faults in hydraulic servo system, the first-stage RBF observer and the second-stage RBF localizer should be trained sufficient in all possible fault conditions.

2.3 RBF neural network mathematical model

As shown in Fig.2, the RBF neural network is a three-layer feedforward network, including the input layer, the output layer and the hidden layer. The nodes in adjacent layers are full connected. $x_i(i=1,2,\cdots,n)$ are inputs, $h_i(i=1,2,\cdots,m)$ are activation functions of the hidden layer, and $w_i(i=1,2,\cdots,m)$ are weights of output layer.

In RBF neural network, the mapping between the input layer and the hidden layer is constructed by Gaussian radial basis function, and the mapping between the output layer and the hidden layer is constructed by linear function. The activation function of the hidden layer nodes locally responds to input signal. That is to say, its activation is maximal when an input is located at the RBF center, while the activation decreases monotonically when the distance between the RBF center and an input increases.

Let the input vector of the first-stage RBF network observer be defined as

$$\boldsymbol{X}=[x_1 \ \ x_2]^{\mathrm{T}}=[r(k-1) \ \ y_{\mathrm{f}}(k-1)]^{\mathrm{T}} \qquad (5)$$

where r is a control signal, and y_{f} is a displacement of the ram.

Let the estimated output $\hat{y}_{\mathrm{f}}$ be defined as

$$\hat{y}_{\mathrm{f}}=\boldsymbol{W}^{\mathrm{T}}\boldsymbol{H}=\sum_{i=1}^{m} w_i h_i \ , \qquad (6)$$

where $\boldsymbol{W}=[w_1 \ \ w_2 \ \ \cdots \ \ w_m]$ is a weight vector of network, and $\boldsymbol{H}=[h_1 \ \ h_2 \ \ \cdots \ \ h_m]$ is a radical basis function vector, and the Gaussian function be generally adopted as follows

$$h_i(x)=\exp\left[-\frac{\|\boldsymbol{x}-\boldsymbol{c}_i\|^2}{2\boldsymbol{\sigma}_i^2}\right] \quad (i=1,2,\cdots,m) \qquad (7)$$

where $\boldsymbol{x}$ is an input vector with n dimensions (here, n=2), $\boldsymbol{c}_i$ is called the center vector of the ith node and has the same dimensions with $\boldsymbol{x}$, $\boldsymbol{\sigma}_i$ is called the bandwidth vector of ith node, m stands for the number of node, and $\|\cdot\|$ denotes the Euclidean norm[4].

Let the input vector of the second-stage RBF network localizer be defined as

$$\boldsymbol{Z}=[z_1 \ \ z_2 \ \ z_3 \ \ z_4]^{\mathrm{T}}=[\boldsymbol{\sigma}_i \ \ \boldsymbol{c}_i \ \ \boldsymbol{w}_i \ \ \boldsymbol{\varepsilon}]^{\mathrm{T}} \qquad (5)$$

where $\boldsymbol{\sigma}_i$ is the ith node bandwidth vector of the first-stage RBF observer, $\boldsymbol{c}_i$ is the ith node center vector of the first-stage RBF observer, $\boldsymbol{w}_i$ is the weights of the first-stage RBF observer, and $\boldsymbol{\varepsilon}$ is the residual error between the first-stage observer output and the system output.

2.4 RBF neural network learning algorithm

Traditional K-means clustering algorithm requires determining the number of the hidden nodes in advance, and the choice of initial clustering centers heavily affects the learning speed of network.

An improved K-means clustering algorithm of obtaining radial basis function centers is presented, which is an on-line self-adaptive clustering algorithm, and need not determine the number of the hidden nodes in advance. The algorithm leaves out the iterative calculation of beforehand determining the number of the hidden nodes, and quickens the clustering. Self-adaptive adjustment algorithm of learning rate is presented to quicken the convergence and to guarantee the stability of the process.

Improved K-means clustering algorithm can be described as follows.

(1) Choose an appropriate Gaussian function width r, and select the first sample $\boldsymbol{X}_1$ as the first clustering center $\boldsymbol{C}_1$, then $\boldsymbol{C}_1=\boldsymbol{X}_1$, and the number of clustering is k=1.Thus the RBF network established has only one hidden node, whose center is $\boldsymbol{C}_1$.

(2) Calculate the distance between the second sample $\boldsymbol{X}_2$ and $\boldsymbol{C}_1$, if $\|\boldsymbol{X}_2-\boldsymbol{C}_1\|<r$, then $\boldsymbol{X}_2$ is grouped under the 1st group and $\boldsymbol{C}_1=\frac{1}{2}(\boldsymbol{X}_2+\boldsymbol{X}_1)$. If $\|\boldsymbol{X}_2-\boldsymbol{C}_1\|>r$, then $\boldsymbol{X}_2$ is selected as the 2nd clustering center $\boldsymbol{C}_2=\boldsymbol{X}_2$ and $k=2$.

(3) When considering the ith sample $\boldsymbol{X}_i$ (i=3,4,$\cdots$,N), the RBF has m hidden nodes, whose clustering centers are $\boldsymbol{C}_1$, $\boldsymbol{C}_2\cdots\boldsymbol{C}_m$. Calculate the distance between $\boldsymbol{X}_i$ and m clustering centers $\|\boldsymbol{X}_i-\boldsymbol{C}_j\|$ $(j=1,2,\cdots,m)$, suppose $\|\boldsymbol{X}_i-\boldsymbol{C}_h\|=\min\limits_j\|\boldsymbol{X}_i-\boldsymbol{C}_j\|$ is the least distance, if $\|\boldsymbol{X}_i-\boldsymbol{C}_h\|<r$, then $\boldsymbol{X}_i$ is grouped under hth class and $\boldsymbol{C}_h=\sum\limits_{\boldsymbol{X}_P\in h}\boldsymbol{X}_P$. And if $\|\boldsymbol{X}_i-\boldsymbol{C}_h\|>r$, then $\boldsymbol{X}_i$ is selected as a new clustering center $\boldsymbol{C}_{m+1}=\boldsymbol{X}_i$ and $k=k+1$.

(4) Go to (3), until all samples are classified and all clustering centers are determined. Adjust the centers according to the K-means clustering algorithm again. Group all samples $\boldsymbol{X}_P(p=1,2,\cdots,P,P$ is the total of samples) according to the nearest clusters centers by using the minimum-distance Euclidean criterion. If

$$\|\boldsymbol{X}_p-\boldsymbol{C}_j^n\|=\min_i\|\boldsymbol{X}_p-\boldsymbol{C}_i^n\| \tag{8}$$

then group $\boldsymbol{X}_p$ under jth class.

(5) Adjust the centers of the radial-basis functions using the update rule

$$\boldsymbol{C}_j^{n+1}=\frac{1}{N_j}\sum_{\boldsymbol{X}_P\in j}\boldsymbol{X}_P \tag{9}$$

where N_j is the number of samples of jth group.

(6) Go back to (4), and continue the procedure until $\boldsymbol{C}_j^{n+1}=\boldsymbol{C}_j^{n}$. Now the clustering centers obtained by K-means clustering algorithm can be used as centers of RBF network.

(7) For each clustering center $\boldsymbol{C}_j$, $\boldsymbol{\sigma}_j$ can be calculated as follows

$$\boldsymbol{\sigma}_j=\frac{1}{N_j}\sum(\boldsymbol{X}_P-\boldsymbol{C}_j)^\tau(\boldsymbol{X}_P-\boldsymbol{C}_j)\,. \tag{10}$$

(8) The weights of output layer are obtained based on LS. Let the objective function be defined

$$E=\frac{1}{2N}\sum_{t=1}^{n}(y_{\mathrm{f}}-\hat{y}_{\mathrm{f}})^{\mathrm{T}}(y_{\mathrm{f}}-\hat{y}_{\mathrm{f}}) \tag{11}$$

According to the LS algorithm, the equation for updating network connecting weights can be obtained as follows[5]

$$W(k)=W(k-1)-\alpha\frac{\partial E}{\partial W(k-1)} \tag{12}$$

In order to quicken the convergence, momentum correction is added to Eq.(12)

$$W(k)=W(k-1)-\alpha\left[(1-\eta)\frac{\partial E}{\partial W(k-1)}+\eta\frac{\partial E}{\partial W(k-2)}\right] \tag{13}$$

where α is the learning rate of network, $0<\eta<1$ is the momentum factor.

Due to the learning rate affects heavily the convergence speed and convergence characteristics, it is difficult to choose.

An improved learning algorithm by adding self-adaptive factor of learning rate is presented here and can be described as follows

$$W(k)=W(k-1)-\alpha(k)\left[(1-\eta)\frac{\partial E}{\partial W(k-1)}+\eta\frac{\partial E}{\partial W(k-2)}\right] \tag{14}$$

$$\alpha(k)=\rho(k)\alpha(k-1) \tag{15}$$

$$\rho(k)=2^\tau\varepsilon \tag{16}$$

where $\tau=\mathrm{sign}\left[\frac{\partial E}{\partial W(k-1)}\cdot\frac{\partial E}{\partial W(k-2)}\right]$, and ε is an error coefficient.

The momentum factor and learning rate self-adaptive factor are added to the network learning algorithm to quicken the convergence. Thus optimum learning rate is obtained by adjusting learning rate self-adaptive factor to ensure the convergence and the stability of algorithm.

2.5 Decision making of fault in hydraulic system

In normal operating conditions, the residual error is approximate to Gaussian flat noise. And its mean is close to zero, the covariance matrix can be described as[6]

$$U(k)=E[\varepsilon(k)\varepsilon^{\mathrm{T}}(k)] \tag{17}$$

where $\varepsilon(k)$ is the residual error of system.

When estimated covariance matrix $U(k)$ varies with time, $U(k)$ has different statistic characteristic with different k, therefore, let another random variable be defined,

$$\xi(k)=U^{-1/2}(k)\varepsilon(k) \tag{18}$$

where $\xi(k)$ is approximate to random vector of flat noise whose mean is close to zero.

Due to the inconvenience in calculating $U^{-1/2}$, let a random variable be defined as

$$\xi^{\mathrm{T}}(k)\xi(k)=\varepsilon^{\mathrm{T}}(k)U^{-1}(k)\varepsilon(k) \tag{19}$$

where $\xi^{\mathrm{T}}(k)\xi(k)$ subjects to X_{m-1}^{2} distribution. The weighted square sum can be obtained as follows

$$b(k)=\frac{1}{N}\sum_{j=K-N+1}^{K}\xi^{\mathrm{T}}(j)\xi(j)=\frac{1}{N}\sum_{j=K-N+1}^{K}\varepsilon^{\mathrm{T}}(j)U^{-1}(j)\varepsilon(j) \tag{20}$$

where N is the length of data window, $b(k)$ is less in normal operating conditions, but in the presence of faults, $b(k)$ will increase, $\xi(k)$ can not satisfy flat noise characteristic.

Fault diagnosis strategy can be described as follows[7]

$$\left.\begin{array}{ll} b(k)\leqslant\alpha & x\in w_0 \\ b(k)>\alpha & x\in w_1 \end{array}\right\} \tag{21}$$

where α is a fault threshold, w_0 is the normal mode of hydraulic servo system, and w_1 is the fault mode of hydraulic servo system.

The choice of fault threshold is a difficult problem in fault diagnosis fields. If chosen too small, when the output noise of the sensor is much larger, it is easy to alarm by mistake. If chosen too large, it is difficult to detect the fault of less amplitude change and easy to fail to alarm[8]. This paper determines the threshold according to the off-line training error of samples and noise standard deviation. In order to eliminate the alarm by mistake caused by output noise of the sensor and learning error, the sum of the maximum off-line training error and three times of noise standard deviation is selected as a fault threshold.

3 Experimental Results

Experiments were carried out to test the RBF fault detection strategy shown in Fig.3.

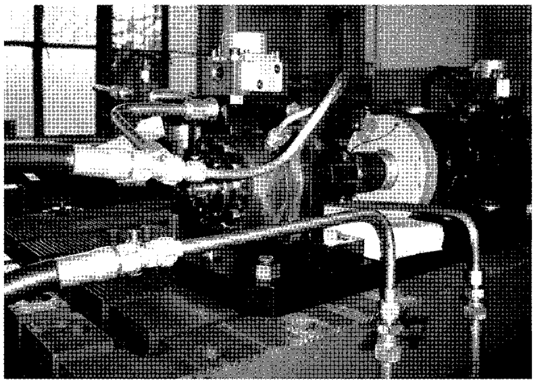

Fig.3 Hydraulic servo system test station

In normal operating conditions, when experimented by a sinusoidal input signal with frequency of 1Hz and amplitude of 20 mm, the estimated output of trained RBF neural network are obtained, the residual error between actual and corresponding estimated output of RBF fault observer is shown in Fig.4. From Fig.4, it can be seen that the RBF neural network observer is effective in tracking the hydraulic servo system. The residual error stays at a relatively low level and is close to zero in normal operating condition. But the overall error of the residuals increases due to the uncertainty of system friction in experiment.

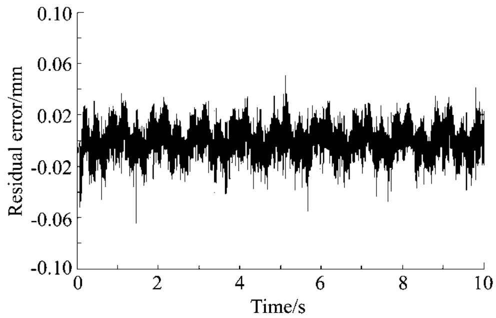

Fig. 4 Experimental residual curve in normal condition

（1）The fault experiment of electric amplifier

According to fault the analysis of hydraulic servo system, it is known that the electric amplifier faults, the servo valve faults and the actuator faults generally represent the sudden change of gain of transfer function in mathematical model. For example, open circuit fault of electric amplifier, lock fault of servo valve and lock fault of the actuator…etc. In order to simulate these faults in actual experiments, the proportion coefficient K_p of PID controller can be set to simulate these faults. The following is the simulation of electric amplifier fault. The increment of proportion coefficient K_p simulates the drifting fault of amplifier. In experiment the proportion coefficient K_p increased by 0.5 at the fifth second, and lasted two seconds. The residual errors suddenly increased and stayed at a recognizably higher level within 0.3 second.

As shown in Fig.5, the residual between the actual and the corresponding estimated outputs of network deviates from normal level when electric amplifier fault occurs. Residual error exceeds the fault threshold, and is 20 times that in normal condition during 5th-7th second. Obviously, the occurrences of amplifier faults can be detected by residual error.

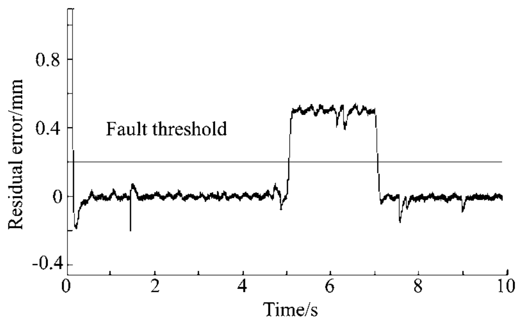

Fig.5　Residual error between actual outputs and corresponding RBF estimates in electric amplifier fault condition

(2) The leakage fault simulation

The leakage fault is one of the faults often occurring in hydraulic servo system. The slide valve abrasion in servo valve and the clearance between the ram and the actuator can cause leakage increase. To simplify, the problem, it is only considered that the leakage fault can be represented by the increase of flow-pressure coefficient K_{ce} in mathematical model. Suppose flow-pressure coefficient is K_{ce}=2.0373×10^{-11} in normal operating condition, and K_{ce} is changed by ΔK_{ce}=2.0373×10^{-11} to simulate leakage faults. Residual error shown in Fig.6 is generated through simulation.

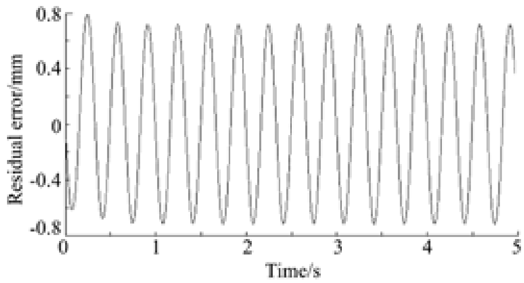

Fig.6　Residual curve of the leakage fault

As seen from Fig.6, the residual error deviates from the normal level and is 40 times larger than that in normal operating condition. Consequently, occurrence of leakage faults can be detected by residual error.

In order to test the localization ability of the second-stage RBF localizer, the residual error and the weight parameters of the first-stage RBF observer in normal, electric amplifier fault and leakage fault conditions are respectively input to the trained second-stage RBF network. The second-stage RBF classifier identifies the fault mode according the input failure feature. The results of diagnosis are shown in Table 1.

Table 1　Fault classification results

Status	Actual output of network			
	1	2	3	4
Normal	0.923 4	0.016 0	0.053 8	0.001 2
Amplifier fault	0.049 9	0.945 1	0.001 4	0.051 5
Leakage fault	0.033 8	0.000 5	0.878 8	0.049 2

As shown in Table 1, the outputs of the fault neural cell are larger, when using the RBF localizer to classify the faults.

It is easy to see that the RBF network succeeds in mapping the failure feature into different faults mode, and realizes the faults classification in hydraulic servo system.

4 Conclusions

A two-stage RBF neural network model is proposed to realize the failure detection and fault localization. Network parameters are determined by improving the K-means clustering algorithm, which obtains the optimum learning rate by self-adaptive adjustment algorithm. The residual errors between the actual measurement and the estimated output of the first-stage RBF observer are used for the fault detection in hydraulic servo system. According to the residual error and structure parameters of the first-stage RBF observer, the second-stage RBF localizer is used to realize the fault localization. Simulation and experiments indicate:

（1）The RBF observer could identify the system model precisely. In normal condition, the nonlinearities and disturbance are memorized by network and distributed among connecting intensity of nerve cell, and there are some redundancies. Therefore the robustness is better. The residual error between the estimated output and actual output is close to zero in normal operating conditions. In the presence of some faults the residual error deviates from zero. When the residual error exceeds the threshold, it is ascertained that faults occur.

（2） Using the residual error and structure parameters of the first-stage RBF observer to localize the faults is effective in fault diagnosis of hydraulic servo system.

（3）The learning rate of RBF neural network heavily affects the identification precision of system. In some cases, the RBF network may diverge because the learning rate is not properly chosen. The improved K-means algorithm and self-adaptive adjustment algorithm of learning rate with additional moment factor are presented to obtain the optimum learning rate, which can avoid the local minimum, guarantee instability and quicken the convergence.

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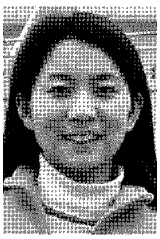
Biography:



LIU Hong-mei Born in 1978, she received B.S. and M.S. from Liaoning Institute of Technology in 2001 and Northeasten University in 2004 respectively, and now is a Ph.D. candidate at Beijing University of Aeronautics and Astronautics. Her research interests focus on the area of electromechanical engineering. E-mail: liuhongmeigg @ asee.buaa.edu.cn.