Research Journal of Applied Sciences, Engineering and Technology 5(16): 4071-4076, 2013
DOI:10.19026/rjaset.5.4627
ISSN: 2040-7459; e-ISSN: 2040-7467
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Submitted: March 23, 2012 Accepted: January 11, 2013 Published: April 30, 2013

Research Article

Fault Diagnosis of Autonomous Underwater Vehicles

[1]Xiao Liang, [2]Jundong Zhang and [3]Wei Li
[1]College of Traffic Equipment and Ocean Engineering,
[2]College of Marine Engineering,
[3]College of Environmental Science and Engineering, Dalian Maritime University, Dalian, China

Abstract: In this study, we propose the least disturbance algorithm adding scale factor and shift factor. The dynamic learning ratio can be calculated to minimize the scale factor and shift factor of wavelet function and the variation of net weights and the algorithm improve the stability and the convergence of wavelet neural network. It was applied to build the dynamical model of autonomous underwater vehicles and the residuals are generated by comparing the outputs of the dynamical model with the real state values in the condition of thruster fault. Fault detection rules are distilled by residual analysis to execute thruster fault diagnosis. The results of simulation prove the effectiveness.

Keywords: Autonomous underwater vehicle, least disturbance, thruster fault diagnosis, wavelet neural network

INTRODUCTION

With the development of the activities in deep ocean, the application of underwater vehicles is widespread (Xu and Xiao, 2007; Blidberg, 1991). Underwater vehicles are frequently performing mission in unstructured, complicated and hazardous environment (Adam, 1985). For autonomous underwater vehicles, the ability to detect and tolerate fault is a crucial issue to realize its autonomy. Model-based technique has the merits such as low cost, high reliability and easy realization for autonomous underwater vehicles, so it is a suitable approach. However, for the influence of model error, measurement noise, outer disturbance and so on, it is difficult enogh to build up the accurate model for autonomous underwater vehicles. Neural network has the characters of strong input-output nonlinear mapping, distributed store of information, parallel process and especially strong self-organizing and self-learning ability, which make neural network become an effective method for fault diagnosis. Moreover, it has been applied in practice (Alessandri *et al*., 1999).

Wavelet neural network is a new radial basis function neural network developed from wavelet transform. The orthonormality of wavelet function used as the hidden layer function makes wavelet neural network more suitable in learning function of local variation and discontinuities. By adjusting scale factor and shift factor of wavelet function and weights of network to affect output of network, wavelet neural network has strong ability of distilling signal details and mapping nonlinear function (Li and Wei, 1998; Zhao and Zhou, 2003). In this study, we propose a least disturbance wavelet neural network to build up the dynamic model of underwater vehicles and add scale factor and shift factor of wavelet function to dynamic learning rate algorithm based on steepest descent method. Then, we compare the output of model with the real state value to achieve residuals and distill the fault information from the residuals to detect fault.

In this study, we propose the least disturbance algorithm adding scale factor and shift factor. The dynamic learning ratio can be calculated to minimize the scale factor and shift factor of wavelet function and the variation of net weights and the algorithm improve the stability and the convergence of wavelet neural network. It was applied to build the dynamical model of autonomous underwater vehicles and the residuals are generated by comparing the outputs of the dynamical model with the real state values in the condition of thruster fault. Fault detection rules are distilled by residual analysis to execute thruster fault diagnosis. The results of simulation prove the effectiveness.

LEAST DISTURBANCE WAVELET NEURAL NETWORK

The common training algorithm of wavelet neural network is steepest descent method and learning rate is extremely significant for the convergence and stability of c network. The hidden layer function of wavelet neural network is wavelet function and its scale factor and shift factor are also adjusted to minimize the least square error. For wavelet neural network, outputs of neural network are affected by both net weights and scale factor and shift factor of wavelet function. From the perspective, we add scale factor and shift factor of wavelet function to the least disturbance dynamic

Corresponding Author: Xiao Liang, Dalian Maritime University, Dalian 116026, China
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learning rate algorithm based on steepest descent method (Liu *et al*., 2001).

Define the input-output relationship of wavelet neural network as:

$$y_i = \sum_j w_{ij}^{(1)} h_j \tag{1}$$

$$h_j = f\left((net_j - b_j)/a_j\right) \tag{2}$$

$$net_j = \sum_k w_{jk}^{(2)} x_k \tag{3}$$

The error function is given by:

$$E = \frac{1}{2}\sum_i (d_i - y_i)^2 \tag{4}$$

where, y_i is the *ith* component of an output vector and h_j denotes the output of *jth* wavelet in hidden layer and net_j denotes the input of *jth* wavelet in hidden layer, x_k is the *kth* component of input vector. d_i is the *ith* desired target output. a_j, b_j is scale factor and shift factor of wavelet function in hidden layer.
Make difference operation for (4) as follows:

$$\begin{aligned} -\Delta E &= \sum_i (d_i - y_i)\Delta y_i = \sum_i (d_i - y_i)\left(\sum_j h_j \Delta w_{ij}^{(1)}\right. \\ &+ \sum_j w_{ij}^{(1)}/a_j f'()\sum_k x_k \Delta w_{jk}^{(2)} - \sum_j w_{ij}^{(1)}/a_j^2 f'() \\ &\left.(\sum_k x_k w_{jk}^{(2)} - b_j)\Delta a_j - \sum_j w_{ij}^{(1)}/a_j f'()\Delta b_j\right) \end{aligned} \tag{5}$$

If we make ΔE = - E through the modifying weight, input-output relationship will satisfy the need of the goal function. However, owing to first-order approximation of the difference operation; there will be errors for nonlinear neural network and it is very hard to get ΔE = - E through once modification, so η is introduced which is usually given by 0< η < 1. ΔE. is defined as:

$$\Delta E = -\eta E = -\Omega \tag{6}$$

where η has the same meaning as the training ratio of the steepest descent method, but the higher certainty is obtained compared with the standard steepest descent method. If the training ratio is selected in the adjacent area of 1, the similar results can be obtained. From (5) and (6), the variation of net weights can be described as:

$$\begin{aligned} &\sum_i (d_i - y_i)\left(\sum_j h_j \Delta w_{ij}^{(1)} + \sum_j w_{ij}^{(1)}/a_j f'(net_j)\cdot\right. \\ &\sum_k x_k \Delta w_{jk}^{(2)} - \sum_j w_{ij}^{(1)}/a_j^2 f'(net_j)(\sum_k x_k w_{jk}^{(2)} - b_j) \\ &\left.\Delta a_j - \sum_j w_{ij}^{(1)}/a_j f'(net_j)\Delta b_j\right) - \Omega = 0 \end{aligned} \tag{7}$$

The solution of (7) is indefinite, namely, there are infinite appropriate solutions. To obtain the definite solution condition, we construct a performance function:

$$J = \sum_{i,j}\frac{1}{2}\Delta w_{ij}^{(1)2} + \sum_{j,k}\frac{1}{2}\Delta w_{jk}^{(2)2} + \sum_j \frac{1}{2}\Delta a_j^2 + \sum_j \frac{1}{2}\Delta b_j^2 \tag{8}$$

The significance to minimize the performance function is to adjust net weights and scale factor and shift factor of wavelet neural network as small as possible and make the current error be zero. The smaller the adjustable value is, the less the disturbance of the previous learning knowledge would be. Therefore, the performance function is called least disturbance function. The equivalent expression of (7) is:

$$\begin{aligned} J &= \sum_{i,j}\frac{1}{2}\Delta w_{ij}^{(1)2} + \sum_{j,k}\frac{1}{2}\Delta w_{jk}^{(2)2} + \sum_j \frac{1}{2}\Delta a_j^2 \\ &+ \sum_j \frac{1}{2}\Delta b_j^2 - \lambda\left[\sum_i (d_i - y_i)\left(\sum_j h_j \Delta w_{ij}^{(1)}\right.\right. \\ &+ \sum_j w_{ij}^{(1)}/a_j f'(net_j)\sum_k x_k \Delta w_{jk}^{(2)} - \sum_j w_{ij}^{(1)}/a_j^2 f'() \\ &\left.\left.(\sum_k x_k w_{jk}^{(2)} - b_j)\Delta a_j - \sum_j w_{ij}^{(1)}/a_j f'(net_j)\Delta b_j\right) - \Omega\right] \end{aligned} \tag{9}$$

where, λ is an unknown coefficient. We can use Lagrange extreme value theory to get the solution which satisfies (7) and minimizes *J*. The algorithm in detail is as follows. To make the derivative of the weight modified value be zero, we can obtain:

$$\frac{\partial J}{\partial \Delta w_{ij}^{(1)}} = \Delta w_{ij}^{(1)} - \lambda(d_i - y_i)h_j = 0 \tag{10}$$

$$\frac{\partial J}{\partial \Delta w_{jk}^{(2)}} = \Delta w_{jk}^{(2)} - \lambda\left[\sum_i (d_i - y_i) w_{ij}^{(1)}/a_j f'() x_k\right] = 0 \tag{11}$$

$$\begin{aligned} \frac{\partial J}{\partial \Delta a_j} &= \Delta a_j + \lambda\left[\sum_i (d_i - y_i) w_{ij}^{(1)}/a_j^2 f'(net_j)\cdot\right. \\ &\left.(\sum_k x_k w_{jk}^{(2)} - b_j)\right] = 0 \end{aligned} \tag{12}$$

$$\frac{\partial J}{\partial \Delta b_j} = \Delta b_j + \lambda\left[\sum_i (d_i - y_i) w_{ij}^{(1)}/a_j f'(net_j)\right] = 0 \tag{13}$$

(10) to (13) can be rewritten as:

$$\Delta w_{ij}^{(1)} = \lambda(d_i - y_i)h_j = \lambda\delta_i^{(1)} h_j \tag{14}$$

$$\Delta w_{jk}^{(2)} = \lambda\sum_i (d_i - y_i) w_{ij}^{(1)}/a_j f'(net_j) x_k = \lambda\delta_j^{(2)} x_k / a_j \tag{15}$$

$$\begin{aligned}\Delta a_j &= -\lambda\left[\sum_i (d_i - y_i) w_{ij}^{(1)} / a_j^2 f'(net_j)\cdot\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)\right] \\ &= -\lambda\delta_j^{(2)}\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)/a_j^2\end{aligned} \tag{16}$$

$$\Delta b_j = -\lambda\left[\sum_i (d_i - y_i) w_{ij}^{(1)} / a_j f'(net_j)\right] = -\lambda\delta_j^{(2)} / a_j \tag{17}$$

Substituting (14), (15), (16) and (17) into (7):

$$\begin{aligned}&\sum_i \delta_i^{(1)}\Bigg(\sum_j h_j \lambda \delta_i^{(1)} h_j + \sum_j w_{ij}^{(1)} / a_j f'(net_j) \\ &\quad \sum_k x_k \lambda \delta_j^{(2)} x_k + \sum_j w_{ij}^{(1)} / a_j^2 f'(net_j) \\ &\quad \left(\sum_k x_k w_{jk}^{(2)} - b_j\right)\lambda\delta_j^{(2)}\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)/a_j^2 \\ &\quad + \sum_j w_{ij}^{(1)} / a_j f'(net_j)\lambda\delta_j^{(2)} / a_j\Bigg) = \Omega\end{aligned} \tag{18}$$

That is:

$$\begin{aligned}&\lambda\sum_i \delta_i^{(1)2}\sum_j h_j^2 + \lambda\sum_j \delta_j^{(2)2}\sum_k x_k^2 / a_j^2 + \\ &\lambda\sum_j \delta_j^{(2)2}\left[\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)/a_j^2\right]^2 + \lambda\sum_j \delta_j^{(1)2} / a_j^2 = \Omega\end{aligned} \tag{19}$$

We can obtain:

$$\lambda = \frac{\Omega}{\sum_i \delta_i^{(1)2}\sum_j h_j^2 + \sum_j \delta_j^{(2)2}\sum_k x_k^2 / a_j^2 + \sum_j \delta_j^{(2)2}\left(\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)/a_j^2\right)^2 + \sum_j \delta_j^{(2)2} / a_j^2} \tag{20}$$

Substituting (20) into (14), (15), (16) and (17), we can obtain the suitable variation of net weights, scale factor and shift factor. Considering when error approaches zero, the numerator and denominator of (20) will both approach zero, we add a small value $\varepsilon > 0$ into the denominator, then we can obtain:

$$\lambda = \frac{\Omega}{\sum_i \delta_i^{(1)2}\sum_j h_j^2 + \sum_j \delta_j^{(2)2}\sum_k x_k^2 / a_j^2 + \varepsilon + \sum_j \delta_j^{(2)2}\left(\left(\sum_k x_k w_{jk}^{(2)} - b_j\right)/a_j^2\right)^2 + \sum_j \delta_j^{(2)2} / a_j^2} \tag{21}$$

The variation of net weights, scale factor and shift factor also use steepest descent method, but since λ will change timely with the current state and the current input of the system, it will be of benefit to the convergence and robustness of the network. From (21), we can conclude that this change will lead to that the reducing of error is always at the suitable level which is determined by η of (6), that is, the reducing of error will not be large to cause unnecessary oscillation and will not be small to cause the convergence too low. On the other hand, since η is equal to the expected reduction ratio of the error, whose value is a little less than 1 which will not influence the convergence of network seriously, but in steepest descent method the convergence is sensitive to the learning ratio.

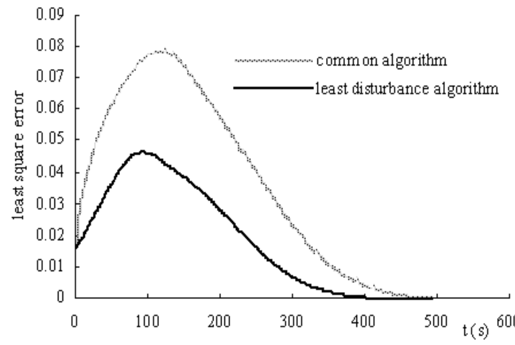

Fig. 1: Effect of trained network in two methods

In the standard steepest descent method, when the number of hidden layer points is added, it is necessary to reduce the learning ratio to assure the convergence of the network. In (21), when $\Sigma_j h_j^2$ is added, λ is reduced simultaneously. While adding the number of hidden layer points means to add $\Sigma_j h_j^2$ and thus λ is reduced. This dynamic learning ratio is helpful for the convergence stability of the network.

With the same initial value of neural network, the effect of two different algorithms is shown as Fig. 1. The training data are from a certain yawing motion of one underwater vehicle. As can be seen, the convergence velocity of the network using least disturbance algorithm is much better.

MODELING USING LEAST DISTURBANCE WAVELET NEURAL NETWORK

The proposed approach has been verified on a certain autonomous underwater vehicle named ZS4 (made in HEU, China) for simulation study. The vehicle has eight thrusters and they can be divided into four groups based on the function of the thrusters: horizontal plane thrusters, vertical plane thrusters, side thrusters and vertical thrusters. Each group has two thrusters. Horizontal and vertical plane thrusters are the ducted thrusters and side and vertical thrusters are the tunnel thrusters. As the velocity increases in the surge direction, thruster deduction becomes serious enough, thus we close four tunnel thrusters in the high velocity to save energy. So in this study, we mainly discuss the thruster fault diagnosis for four main thrusters. Figure 2 shows the thruster configuration of ZS4.

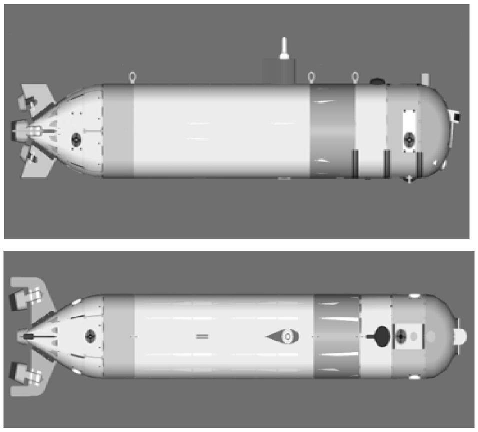

Fig. 2: Thruster configuration of ZS4

The autonomous underwater vehicle is a high coupling system and for identifying each degree, wavelet neural network should be a multi-input and multi-output system. The hidden layer function is defined as the Morlet wavelet:

$$g(x) = \cos(1.75x)e^{(-x^2/2)} \tag{22}$$

ZS4 autonomous underwater vehicle is equipped with Doppler Velocity Log (DVL) to measure three-dimensional linear velocity and compass to measure three-dimensional angles. Considering the sensors and the execution equipments and simplifying the approximating model of neural network, we define the input and output as:

$$\mathbf{u}(k-1) = \left[X_T(k-1) \quad Y_T(k-1) \quad Z_T(k-1) \quad M_T(k-1) \quad N_T(k-1) \quad K_T(k-1)\right]$$

$$\mathbf{y}(k) = [u(k) \quad v(k) \quad w(k) \quad roll(k) \quad pitch(k) \quad yaw(k)]^T \tag{23}$$

where, u, v w are linear velocity in surge, sway and heave direction. *roll*, *pitch*, *yaw* are angular velocity in roll, pitch and yaw direction. X_T, Y_T, Z_T, N_T, K_T, are force/moment in surge, sway, heave, roll, pitch and yaw direction. From the input and output, we can realize 6-DOF nonlinear model identification.

The neural network structure is 6×60×6. We train wavelet neural network offline. Initializing the parameters of wavelet neural network is an important issue and for the parameter learning rate, we use the dynamic approach above. For the scale factor and shift factor, we apply the approach in Zhao and Zhou (2003).

According to the wavelet theory, given t^*as the time domain center, $\Delta\psi$ as the mother wavelet radius. The time domain is given by:

$$[b + at^* - b\Delta\psi, b + at^* + b\Delta\psi] \tag{24}$$

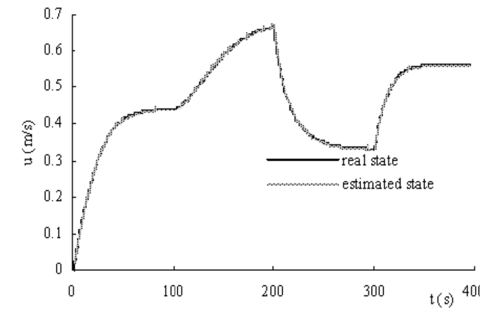

Fig. 3: North velocity output of trained network

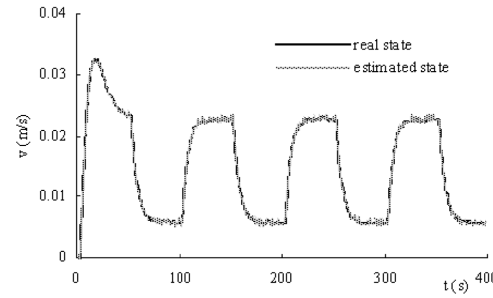

Fig. 4: South velocity output of trained network

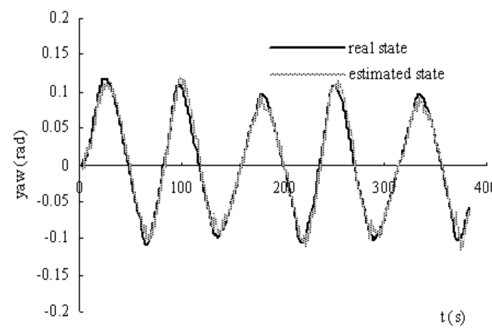

Fig. 5: Yaw output of trained network

In order to guarantee that the wavelet extends initially over the whole input domain, the scale factor and shift factor should satisfy the following equations:

$$\begin{cases} b_j + a_j t^* - a_j \Delta\psi = \sum_{i=1}^{I} w_{ji} x_{i\min} \\ b_j + a_j t^* + a_j \Delta\psi = \sum_{i=1}^{I} w_{ji} x_{i\max} \end{cases} \tag{25}$$

Thus:

$$\begin{cases} a_j = \dfrac{\sum_{i=1}^{I} w_{ji} x_{i\max} - \sum_{i=1}^{I} w_{ji} x_{i\min}}{2\Delta\psi} \\ b_j = \dfrac{\sum_{i=1}^{I} w_{ji} x_{i\max}(\Delta\psi - t^*) - \sum_{i=1}^{I} w_{ji} x_{i\min}(\Delta\psi + t^*)}{2\Delta\psi} \end{cases} \tag{26}$$

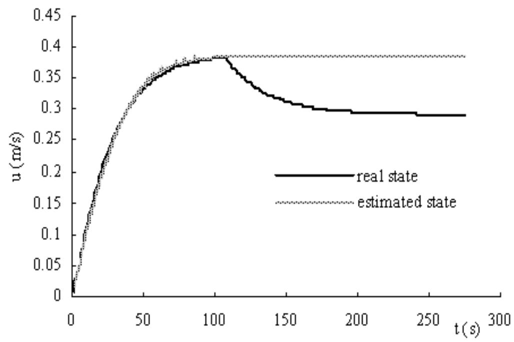

Fig. 6: North velocity of left thruster fault experiment

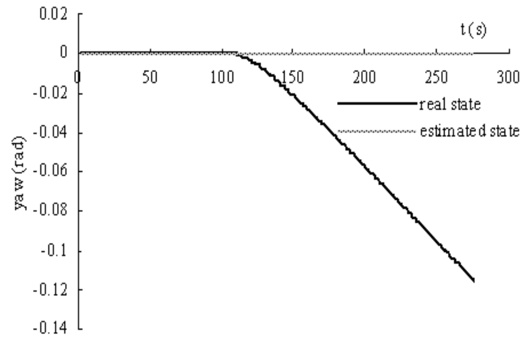

Fig. 7: Yaw of left thruster fault experiment

The net weights is less critical and the parameters are initialized to small random value between [-1, + 1].

The training data are from the simulation experiments such as surging, yawing, swaying and so on. The trained neural network can simulate the motion of the autonomous underwater vehicle very well. The Fig. 3, 4 and 5 show the results and we can see that the least disturbance wavelet neural network can approximate the whole function outline and also distill the change detail.

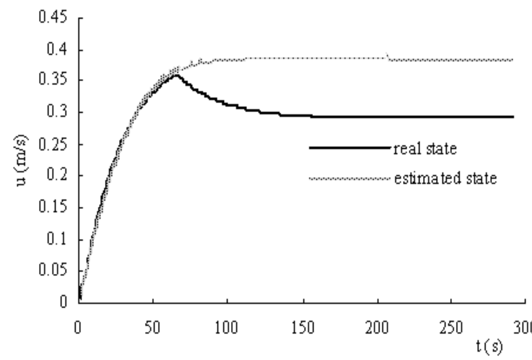

Fig. 8: North velocity of right thruster fault experiment

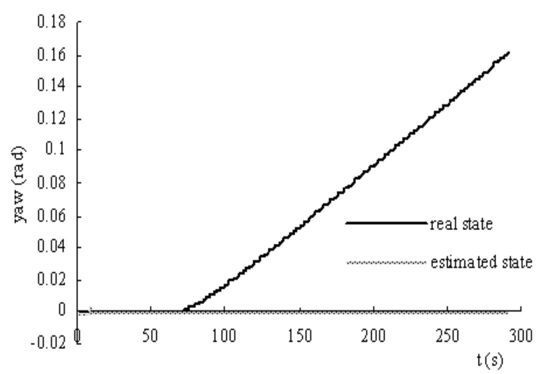

Fig. 9: Yaw of right thruster fault experiment

ANALYSIS OF SIMULATION RESULTS

Comparing the outputs of wavelet neural network with the real state values, we can obtain the residuals and analyze them to distill fault information. To minimize the effect of environment noise, the residuals are analyzed as: in a solid period of gathering a group of residuals, max value and min value are cut and the mean valve of the left data is used as the threshold value. The period and the threshold value are based on plenty of experiments. If the residual is beyond the threshold value, we consider there occurs a fault.

In simulation, the faults of the thrusters are considered as zero outputs of the controller. Simulation is shown as the example of setting a fault of a certain thruster in certain time and then analyzing the residuals. Figure 6, 7, 8 and 9 show the real state values and the outputs of wavelet neural network in the fault of the left or the right thruster when the autonomous underwater vehicle surges. We can see when the main thruster has a fault, the surge velocity changes and the change increases to a steady value as time goes. Meanwhile, the yaw value increases infinitely. For the fault of the left thruster, the yaw is negative. For the fault of the right thruster, the yaw is positive. So we can set one threshold value for each degree. If both the residual of the real velocity and the estimated velocity and the residual of the real yaw and the estimated yaw are beyond the separate threshold value and the yaw residual is negative, the left thruster has a fault. If both the residual of the real velocity and the estimated velocity and the residual of the real yaw and the estimated yaw are beyond the separate threshold value and the yaw residual is positive, the right thruster has a fault. For the other thrusters, the approach is the same.

CONCLUSION

Aiming at the character that hidden layer wavelet function of wavelet neural network can adjust scale factor and shift factor to affect output of the network, the least disturbance algorithm adding scale factor and shift factor is proposed. The algorithm can calculate the dynamical learning ratio to improve the stability and the convergence of the wavelet neural network. Meanwhile, for strong ability of distilling signal details and mapping nonlinear function of wavelet neural network, the algorithm is applied to build the dynamical model of the autonomous underwater vehicle and the residuals are achieved by comparing the outputs of the neural network with the real state values. Fault detection rules are distilled from the residuals to execute actuator fault diagnosis. The results of simulation prove the approach is effective.

ACKNOWLEDMENT

This study is supported by the National Natural Science Foundation of China (Grant No. 51209025) and the China Postdoctoral Science Foundation (Grant No. 20110491519) and Fundamental Research Funds for the Central Universities of China (Grant No. 2011QN130) and Special Fund for Marine Scientific Research in the Public Interest (Grant No. 201005010).

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