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Neural Network Based Rudder-Roll Damping Control System for Ship

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Abstract : *In this paper, new application of adaptive neural network to design a ship's Rudder-Roll Damping(RRD) control system is presented. Firstly, the ANNAI neural network controller is presented. Secondly, new RRD control system using this neural network approach is developed. It uses two neural network controllers for heading control and roll damping control separately. Finally, Computer simulation of this RRD control system is carried out to compare with a linear quadratic optimal RRD control system; discussions and conclusions are provided. The simulation results show the feasibility of using ANNAI controller for RRD. Also, the necessity of mathematical ship model in designing RRD control system is removed by using NN control technique.*

Key words : *Adaptive neural networks, Heading control, Rudder-roll damping control. NN controller*

1. Introduction

During navigation at sea, it is important to reduce the roll of ship caused by environmental effects, because heavy roll motion may harm the ship structure, cargoes as well as crew and passengers' health. Especially, for warship it is very important to get the targets. The methods using stabilizing fins, ballast tanks and rudder for roll damping have been discussed by several researchers. The systems which combine stabilizing fins with rudder have been also proposed (Hearns and Blanke, 1998).

In the late 1970s, Rudder-Roll Damping (hereinafter called RRD) was first suggested. And in the early 1980s, researches showed that it was indeed feasible to control the heading of a ship with at least one rudder while simultaneously using the rudder for roll damping (Fossen, 2002). The researches and applications of RRD control systems to practices which were summarized in Fossen (2002) showed the development in control methods and techniques of this field of study. From 1990s to date, RRD has been analyzed by several authors, for instance in Stoustrup *et al.* (1995), Yang and Blanke (1997), Park and Ohtsu (1998), Hearns and Blanke (1998), Lauvdal and Fossen (1998), Yang and Blanke (1998), Lee *et al.* (2005). The investigations have shown that the roll reduction highly depends on the dynamics of the ship. It was also noted in Yang and Blanke (1997) that the design of a RRD controller with appropriate robust performance to deal with uncertainties in ship model is necessary.

Considering the above literature summation we can see that, no or very few papers on the applications of "intelligent" control, especially neural network (hereinafter called NN) control, to RRD have been found. The potential advantages of NN control and its applications to some marine control problems have been investigated in Nguyen (2007). This study showed the ability of the NN controllers in dealing with nonlinear dynamics of ships as well as uncertainties in ship model and external disturbances.

The main motivation of this paper is to remove the necessity of a mathematical ship model in designing RRD control systems by using NN control technique. The RRD control system proposed in this paper is desired to cope with nonlinear dynamics of ships as well as uncertainties in ship model and external disturbances.

Firstly in this paper, the NN controller similar to that of Nguyen (2007) is presented. Secondly, a RRD control system using this NN approach is developed. It uses two NN controllers for heading control and roll damping control separately. Finally, computer simulation of this RRD control system is carried out to compare with a linear quadratic optimal RRD control system; discussions and conclusions are then provided. The simulation results show the feasibility of the proposed NN control approach in designing RRD control system for ships.

2. General Configuration of NN Controller

It is shown in Brandt and Lin (1999) that, using the

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standard notations as follows, for $i, j \in$ N,

O_i : the output of neuron i;

I_i : the input of neuron i;

θ_i : the threshold value of neuron i;

w_{ij} : the weight of the connection from neuron j to neuron i ; w_{ij} = 0 if j is not connected to i.

$g(x)$: the activation function of a neuron;

O_i^d : the desired output of neuron i (for output neurons);

γ : the learning rate;

the NN can be described by

$$I_i = \sum_{j \in N} w_{ij} O_j + \theta_i \tag{1}$$

$$O_i = g(I_i) = g\left(\sum_{j \in N} w_{ij} O_j + \theta_i\right) \tag{2}$$

The goal is to minimize the following error

$$E = \frac{1}{2} \sum_{i \in N} e_i^2 \tag{3}$$

where $e_i = O_i^d - O_i$, if i is output neuron.

And the adaptation algorithm for NN in Brandt and Lin (1999) can be described as the following

$$\dot{w}_{ij} = \acute{g}(I_i) \frac{O_j}{O_i} \sum_{k \in N} w_{ki} \dot{w}_{ki} - \gamma \acute{g}(I_i) O_j e_i \tag{4}$$

where $\dot{w}_{ij}$ is the increment of weights, $\acute{g}(I_i)$ is derivative of $g(I_i)$ with respect to I_i.

Equation (4) describes Brandt-Lin algorithm for adaptation of weights in NN. Based on this adaptation law and direct NN control scheme developed in Zhang *et al.* (1997), the author proposed in Nguyen (2007) an adaptive NN by adaptive interaction (hereinafter called ANNAI) and applied to ship control.

The configuration of the ANNAI used in this paper is shown in Fig. 1. Using the cost function described in Zhang *et al.* (1997) we have

$$E_k = \frac{1}{2}(X_k^d - X_k)^T P (X_k^d - X_k) + \frac{1}{2} u_k^T \Lambda u_k \tag{5}$$

where X_k^d and X_k are desired state vector and actual state vector respectively; u_k^c is the command control vector and u_k is the actual control vector; P is a real symmetric positive semi-definite matrix reflecting the weightings of the plant variables to be controlled; Λ is a real symmetric positive definite matrix for the control vector.

Similarly in Zhang *et al.*(1997), the training process of the network is carried out within each control cycle indicated by k with n being the number of the training iterations. The adaptation algorithm (4) is used to adjust the synaptic weights in the NN so that, cost function E_k can be minimized. The inputs to the NN controller consist of error $e_k = X_k^d - X_k$ and its time delayed values. The task of the NN controller is to infer appropriate control actions in the next time step after "learning" the behavior of the plant's desired and actual states through e_k.

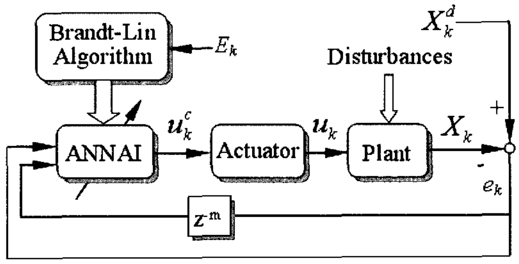

Fig. 1 General configuration of the ANNAI-based control system trained by Brandt-Lin algorithm

3. ANNAI-based RRD Control System

The ANNAI controller is a multi-layer feedforward NN with one hidden layer. The configuration of ANNAI controller is shown in Fig. 2, where w_{ij} is used to indicate the weights between output layer and hidden layer, and w_{jp} is used to indicate the weights between hidden layer and input layer. In general, the subscripts p, j and i indicate the number of neurons in input, hidden and output layers respectively. Based on this ANNAI controller we develop a RRD control system shown in Fig. 3.

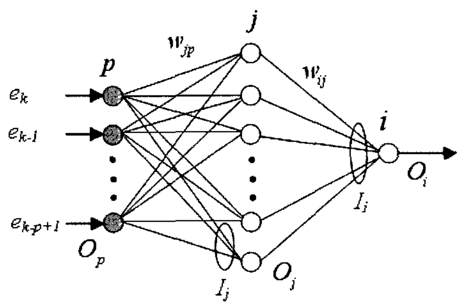

Fig. 2 The ANNAI controller configuration (feedforward NN with one hidden layer)

It has been shown in Stoustrup *et al.* (1995) that a robust RRD controller can be designed by separating the roll and steering specifications and then optimizing the two controllers independently. This investigation suggests that

$$\delta_k = \delta_{1k} + \delta_{2k} \tag{6}$$

where δ_{1k} is output of heading controller, δ_{2k} is output of roll damping controller. The block diagram of the ANNAI-based RRD control system proposed in this paper is shown in Fig. 3, where ANNAI_1 controls ship heading (minimizing E_{1k}), and ANNAI_2 controls ship roll damping (minimizing E_{2k}) separately.

The cost function for ANNAI_1 has the following form

$$E_{1k} = \frac{1}{2}\left[\rho_1(\psi_k^d - \psi_k)^2 + \lambda_1\delta_{1k}^2 + \sigma_1 r_k^2\right] \tag{7}$$

while the cost function for ANNAI_2 has the form as follows

$$E_{2k} = \frac{1}{2}\left[\rho_2(\phi_k^d - \phi_k)^2 + \lambda_2\delta_{2k}^2 + \sigma_2 q_k^2\right] \tag{8}$$

where, ψ_k^d and ϕ_k^d are desired heading and roll angle of ship; ψ_k and ϕ_k are actual heading and roll angle of ship; δ_k^c is command rudder angle; δ_k is actual rudder angle; r_k and q_k are yaw rate and roll rate, respectively ($r_k = \dot{\psi}_k$, $q_k = \dot{\phi}_k$); ρ_i, λ_i, σ_i (i = *1, 2*) are positive constants. The control objective is simultaneous heading control ($\psi_k = \psi_k^d$ =constant) and RRD ($q_d = 0$, $\phi_d = 0$).

Similar to the work of Nguyen (2007), after some mathematical manipulations ANNAI_1 has adaptation laws for the weights of neurons in hidden and output layers expressed by (9) and (10) respectively

$$\dot{w}_{1jp} = O_{1p} \cdot w_{1ij} \cdot \dot{w}_{1ij} \cdot sig(-I_{1j}) \tag{9}$$

$$\dot{w}_{1ij} = \gamma_1 \cdot O_{1j} \cdot (\rho_1 e_{1k} + \lambda_1\delta_{1k} + \sigma_1 r_k) \tag{10}$$

where,

$$sig(-I_{1j}) = \frac{1}{1 + exp[-(-I_{1j})]} \tag{11}$$

and ANNAI_2 has adaptation laws for the weights of neurons in hidden and output layers expressed by (12) and (13) respectively

$$\dot{w}_{2jp} = O_{2p} \cdot w_{2ij} \cdot \dot{w}_{2ij} \cdot sig(-I_{2j}) \tag{12}$$

$$\dot{w}_{2ij} = \gamma_2 \cdot O_{2j} \cdot (\rho_2 e_{2k} + \lambda_2\delta_{2k} + \sigma_2 q_k) \tag{13}$$

where,

$$sig(-I_{2j}) = \frac{1}{1 + exp[-(-I_{2j})]} \tag{14}$$

$$e_{1k} = \psi_k^d - \psi_k \tag{15}$$

$$e_{2k} = \phi_k^d - \phi_k \tag{16}$$

Number of training iterations in one control cycle of ANNAI_1 and ANNAI_2 are respectively indicated by n_1 and n_2. Further details of the ANNAI controllers and their training method can be found in Nguyen (2007).

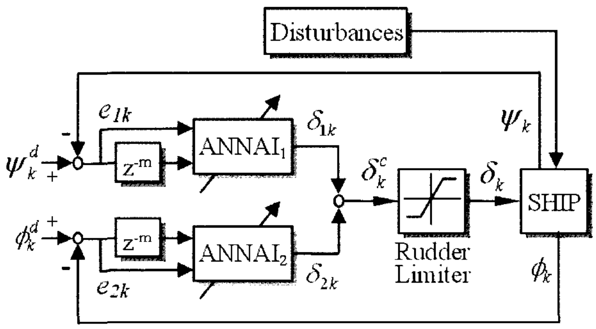

Fig. 3 Configuration of the proposed ANNAI-based RRD control system

4. Simulation Results

In this section, to compare with the proposed ANNAI-based RRD control system we reproduce the simulation results of a linear quadratic optimal RRD control system introduced in Fossen (2002) using the accompanied GNC Toolbox for Matlab. We use the same nonlinear model of the container ship for our simulation to test the performance of ANNAI-based RRD control system. The ship has length of L = 175m, displacement volume of 21,222 m^3. The ship is moving at service speed u_0 = 7.0m/s. The limitation of the steering machine is $\dot{\delta}_{\max} = 20deg/s$ and $\delta_{\max} = 20deg$.

The parameters used for simulations are selected as follows (p = 4, j = 6, i = *1*)

$[\rho_1, \lambda_1, \sigma_1] = [0.5, 0.25, 23.5]$

$[\rho_2, \lambda_2, \sigma_2] = [0.55, 0.25, 9.25]$

In this paper we use fixed values of learning rate ($\gamma_1 = \gamma_2 = 0.8925$) and number of training iterations ($n_1 = n_2 = 60$). The initial heading of ship is 0° and desired heading is 10°. During the first 1000s only heading control function is used. After 1000s RRD control function is turned on.

The simulation results of heading control and roll damping of the linear quadratic optimal RRD control system and the proposed ANNAI-based RRD control system are shown in Figs. 4 and 5 respectively. To evaluate the roll reduction we use the criterion of Oda *et al.* presented in Fossen (2002) as

$$\text{roll reduction} = \frac{d_{AP} - d_{RRD}}{d_{AP}} \times 100\,(\%) \tag{17}$$

where d_{AP}, d_{RRD} are standard deviation of roll rate during course-keeping with RRD function off and on, respectively.

It is observed in Fig. 5 that, during the first 1000s heading control function performs well as already shown in Nguyen (2007), but rolling angle is large. After 1000s the RRD function is active, we can see the effect of $ANNAI_2$ controller. The rudder moves actively for roll damping. As a result, rolling angle and rate is reduced. The roll reduction of the case studies in Fig. 4 and Fig. 5 are of approximately 35.3(%) and 38.6(%).

To test the ability of proposed ANNAI-based RRD control system in severe environmental condition, we increase the effect of wave to ship motions. The simulation results of linear quadratic optimal RRD control system and proposed ANNAI-based RRD control system are shown in Fig. 6 and Fig. 7 respectively. It is shown that yawing motion in Fig. 7 is smaller than one in Fig. 6, and rolling motion is also less. The roll reduction in Fig. 6 and Fig. 7 are of approximately 33.1(%) and 39.2(%).

Through case studies in Fig. 4 ~ Fig. 7, the ANNAI-based RRD control system shows a good ability in heading control and roll damping. Its performance under the effect of wave is improved in comparison with the linear quadratic optimal RRD control system. These advantages can be explained by the ability of ANNAI controllers in optimizing and in coping with nonlinearities ship model as well as environmental effects.

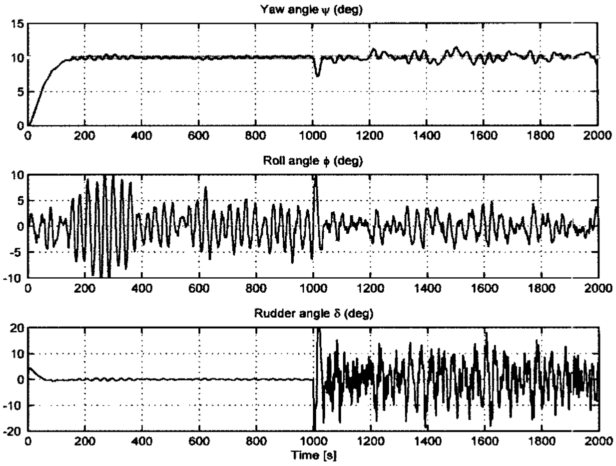

Fig. 4 Simulation results of linear quadratic optimal RRD control system

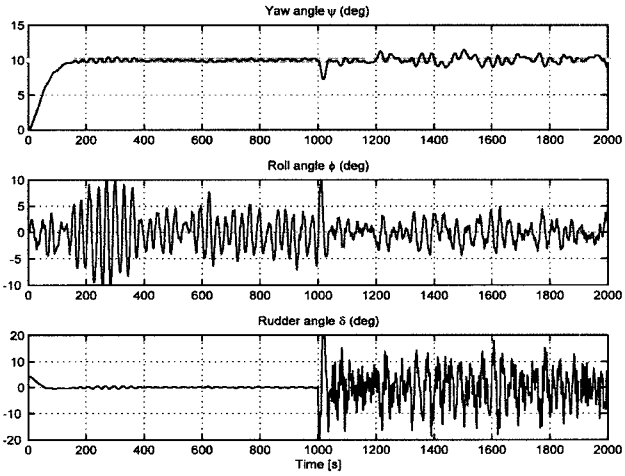

Fig. 5 Simulation results of the proposed ANNAI-based RRD control system

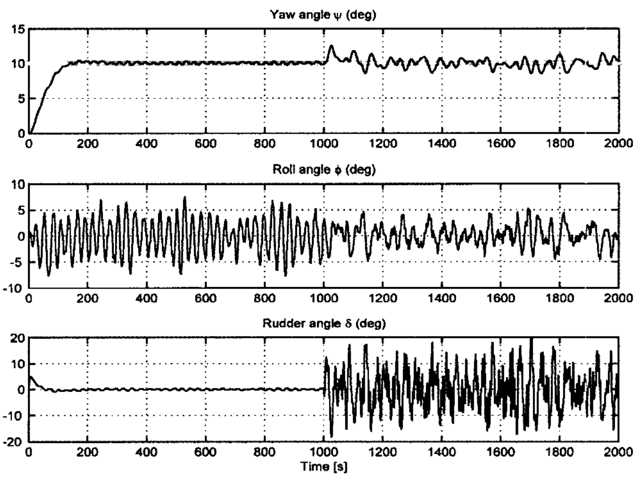

Fig. 6 Simulation results of the linear quadratic optimal RRD control system in stronger wave

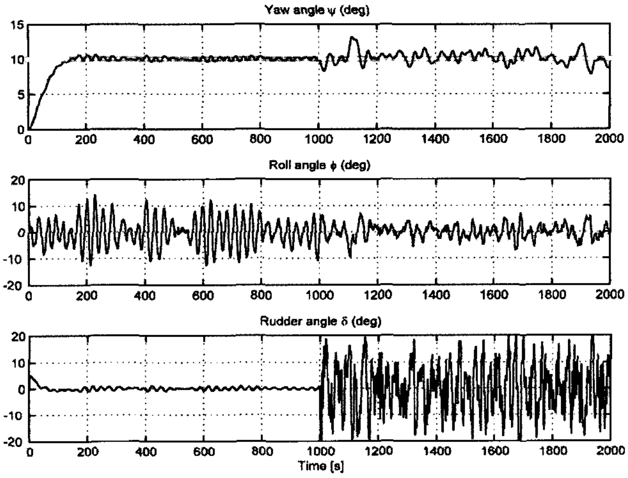

Fig. 7 Simulation results of the proposed ANNAI-based RRD control system in stronger wave

5. Discussion and Conclusion

Simulation results have shown the performance of proposed ANNAI-based RRD control system. It can fulfill the course changing and keeping task. When RRD function is active, the control system can reduce ship rolling motion simultaneously. The ability of roll reduction indicated by equation (17) is better or at least similar to that of the carefully-designed linear quadratic optimal RRD control system.

It is also observed that the heading control performance is degraded during RRD. Additional yawing motion with amplitude of about 1-2 degrees is the price paid for roll damping function added to heading control system. Through these computer simulations, the feasibility of using the ANNAI controller for RRD has been shown. The necessity of a mathematical ship model in designing RRD control system is removed by using NN control technique. As presented in Zhang *et al.* (1997) and Nguyen (2005), the online-trained NN control scheme can help to cope with nonlinear dynamics of ships as well as uncertainties in ship model and external disturbances.

Future study will investigate the performance of proposed ANNAI-based RRD control system in more complicated environmental conditions. A further study on the adaptive ANNAI-based RRD control systems which can adapt to changeable environmental conditions is also recommended.

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