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Study of Ship Heading Control using RBF Neural Network

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Abstract

Along with the development of shipping business, ships are becoming bigger, faster and more intelligent. Thus better performance of maneuver is demanded. To research for better control strategies, it is necessary to adopt new control theories and techniques. The application of neural network techniques and backstepping algorithm in ship motion control became an important research area in recent years. Aiming at the nonlinear of ship motion, also for application of control strategy, control strategy based on the RBF neural network and backstepping algorithm is proposed. The strategy employs the RBF neural network to approximate and substitute the system, and employs adaptive law designed by backstepping algorithm to adjust the weight of the RBF neural network. Finally, the proposed strategy was applied in ship course tracking control simulation and the satisfying performances demonstrate the feasibility and effectiveness of the ship control strategy.

Keywords: *heading control; backstepping; RBF neural network*

1. Introduction

Ship motion control is a both ancient and modern research subject. Ship motion has the characteristics of nonlinear, large time delay and large inertia. The change of the ship heading has had a negative effect to seaworthiness of the vessel, to the safe navigation of ships, equipment, goods on board the ship and crew. In addition, in order to reach the destination as soon as possible and to save energy, it must reduce the course deviation.

The works of Isidori [1], Jakubczyk and Respondek [2] initiated a surge of interest in feedback linearization and more generally in the application of differential geometry to nonlinear control [1, 3]. Recently, the area of robust nonlinear control has received a great deal of attention in the literature. Many methods employ a synthesis approach where the controlled variable is chosen to make the time derivative of a Lyapunov function candidate negative definite. Corless and Leitmann [4] have applied this approach to open-loop stable mismatched nonlinear systems. Several representative results in the early stage of the adaptive control of nonlinear systems were given in [5, 6]. In these papers, the systems are required to satisfy some assumptions such as matching condition, extended matching condition, or growth condition. More recent results without relying on these assumptions can be found in [7-11], to name just a few. In these papers, the backstepping technique was used to synthesize adaptive control laws for strictly feedback systems or lower triangular systems. For systems with high uncertainty, for example, the uncertainty that cannot be linearly parameterized or is completely unknown, various adaptive control methods were further developed in [12, 13] by means of neural network based backstepping techniques. The controllers can achieve bounded tracking error for bounded initial states.However, a drawback with the backstepping technique is the problem of "explosion of complexity". That is, the complexity of controller grows drastically as the order n of the system increases. This "explosion of complexity" is caused by the repeated differentiations of certain nonlinear functions. Due to the introduction of the RBF neural network to approximate the unknown functions and the presence of the approximation

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errors of the unknown functions by the neural networks in the resulting closed-loop system, we have to make extra efforts to establish the stability of the closed-loop system.

According to the characteristics of ship motion control, the structure design and learning algorithm of RBF neural network is the targeted research, and the neural network with the backstepping in study and explore the integrated application of ship motion control and seek effective control strategy, in order to help to enrich and expand the application of neural network in ship control. Firstly, Norrbin nonlinear ship motion model is the research object. Secondly, the specific structure and parameters of RBF network is determined. Thirdly, controller is designed by backstepping, considering the uncertainty of model parameters. Finally through the simulation results of PID control and the backstepping control comparison, after adding interference or model parameters changing, the later control effect is better than the former, the practicability of the backstepping controller and robustness are verified.

2. Ship Motion Mathematical Model

Ship motion mathematical model is the key of the study of ship motion and the design of ship control system. It can be divided into nonlinear mathematical model and the linear mathematical model. Ship motion mathematical model will be introduced below.

2.1. Norrbin Nonlinear Ship Motion Model

Norrbin put forward a nonlinear ship motion mathematical model. The model not only can apply to changing motion variables, and as a kind of theory and experience of the model, it depends on the fluid dynamics on a deeper level.[14] Norrbin model is adopted as the research object in this paper.

In order to improve the precision of the model, Norrbin adviced with spiral maneuvering test of the model of nonlinear term $H(\dot{\psi})$ instead of $\dot{\psi}$ of Nomoto, $H(\dot{\psi})$ will describe the nonlinear control characteristics of ship:

$$H(\dot{\psi}) = n_3\dot{\psi}^3 + n_2\dot{\psi}^2 + n_1\dot{\psi} + n_0 \tag{1}$$

where, $n_i(i = 0,1,2,3)$ called Norrbin coefficient. For vessels with symmetrical hull, $n_2 = n_0 \approx 0$.

This can be

$$H(\dot{\psi}) = n_3\dot{\psi}^3 + n_1\dot{\psi} \tag{2}$$

The corresponding Norrbin nonlinear ship motion model is usually written in the following form:

$$T\ddot{\psi} + \alpha\dot{\psi}^3 + \beta\dot{\psi} = K\delta \tag{3}$$

where, α , β called Norrbin coefficient, can be obtained by spiral test.

2.2. Ship Model Parameter Selection

This paper adopted the training ship "Yu Long" as an example of simulation research. The parameters of "Yu Long" are shown in Table 1. When the ship sailing speed is 7.2 m/s, the Norrbin nonlinear ship motion model of nominal parameters are calculated, $T = 261.73$, $K = 0.42$/s, $\alpha = 30\,s^2$, $\beta = 1$. Using Matlab language to write the fourth-order runge-kutta method and the numerical procedures, mathematical model is programmed, considering rudder Angle range for -30° to +30°, rudder Angle velocity range of -2.5°/s to +2.5°/s.

Table 1. The Parameters of "Yu Long".

Coefficient	Value	Coefficient	Value
L/m	126	Z	4
B/m	20.8	θ	0.67
d/m	8.0	A_R/m^2	18.8
C_B	0.681	H/m	6.1
D_P/m	4.6	H_R/m	3.08
P/m	3.66	λ	1.72

3. The Design of the Ship Course Controller

Ship course control problem is discussed below. Using neural network to identify the ship model, combined with the adaptive backstepping design controller, the ship course controller design is completed.

The backstepping design method is suitable for strict feedback or a lower triangular structure of nonlinear system, the basic idea is that nonlinear system is decomposed into no more than the subsystem of the system order, see some state variables as virtual control, then each subsystem of the Lyapunov function and intermediate virtual control quantity are designed. Subsystem must pass in front of the back of the subsystem of the virtual control can achieve calm. It has been pushed to the actual control of the whole system, step by step correction algorithm stabilization controller is designed, to complete the global regulation or tracking system to the whole system. This paper adopts adaptive backstepping design controller [15][16].

Consider Norrbin nonlinear model of the ship

$$D\ddot{\psi} + C\dot{\psi} + F = \delta \tag{4}$$

where, $D = T/K$, $C = \beta/K$, $F = (\alpha/K)\dot{\psi}^3$, ψ is the bow wave Angle, δ is the rudder Angle, namely the control input, control system block diagram as shown in Figure 1.

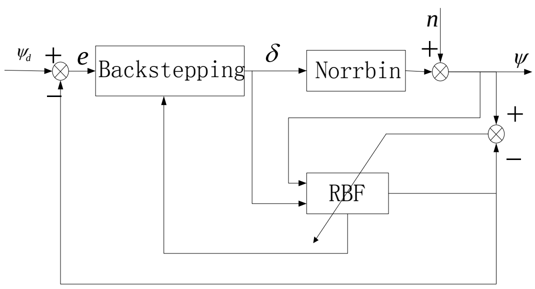


Figure 1. Control System Block Diagram

This is a strict second order feedback system strictly, and nonlinear function all appear in the space of the control input form, adopts the adaptive backstepping design controller, design steps are as follows.

First, define the tracking error

$$e = \psi_d - \psi \tag{5}$$

where, ψ_d is a given course.
Define the error function

$$r = \dot{e} + k_1 e \tag{6}$$

where, $k_1 > 0$, then

$$\dot{\psi} = -r + \dot{\psi}_d + k_1 e \tag{7}$$

$$\begin{aligned} D\dot{r} &= D(\ddot{\psi}_d - \ddot{\psi} + k_1 e) = D(\ddot{\psi}_d - \ddot{\psi} + k_1 e) - D\ddot{\psi} = D(\ddot{\psi}_d - \ddot{\psi} + k_1 e) + C\dot{\psi} + F - \delta \\ &= D(\ddot{\psi}_d - \ddot{\psi} + k_1 e) - Cr + C(\dot{\psi}_d + k_1 e) + F - \delta = -Cr - \delta + f \end{aligned} \tag{8}$$

where, $f(x) = D(\ddot{\psi}_d + k_1 e) + C(\dot{\psi}_d + k_1 e) + F$.

Step 1: try to construct the Lyapunov function

$$V_1 = \frac{1}{2} D r^2 \tag{9}$$

then

$$\dot{V}_1 = D\dot{r}r = (-Cr - \delta + f)r = -Cr^2 - \delta r + fr \tag{10}$$

In practical engineering, the model uncertainties f are unknown, therefore, it needs to close to uncertainties f. Design the control law

$$\delta = \hat{f} + k_2 r \tag{11}$$

where, $\hat{f}(x)$ is approximation of the RBF network output value f, $\tilde{f} = f - \hat{f}$ is the estimation error.

Then

$$\dot{V}_1 = -(C + k_2) r^2 + \tilde{f} r \tag{12}$$

Under the condition of fixed k_2, the stability of the control system relies on the approximation accuracy of $\hat{f}$.

Step 2: using RBF network to approximate f, the algorithm is

$$h_j = \exp\left(-\frac{\left\| X - C_j \right\|^2}{2b_j^2} \right), j = 1, 2, \cdots, m \tag{13}$$

$$f^* = W^{*T} H, f(x) = W^{*T} H + \varepsilon \tag{14}$$

where, $H = [h_1, h_2, \cdots, h_m]^T$, ε is neural network approximation error, W^* is the ideal weights of RBF network, x is the network's input signal, according to the expression $f(x)$, input is

$$x = [e^T \quad \dot{e}^T \quad \psi_d^T \quad \dot{\psi}_d^T \quad \ddot{\psi}_d^T] \tag{15}$$

Using RBF network to approximate f, then the RBF neural network output is

$$\hat{f}(x) = \hat{W}^T H \tag{16}$$

$$\tilde{W} = W^* - \hat{W}, \left\| W^* \right\| \le W_{\max} \tag{17}$$

Constructing final Lyapunov function:

$$V_2 = V_1 + \frac{1}{2}\tilde{W}^T F_w^{-1} \tilde{W} \tag{18}$$

where, F_W is positive definite matrix. Then

$$\dot{V}_2 = D\dot{r}r + \tilde{W}^T F_w^{-1} \dot{\tilde{W}} \tag{19}$$

$$\dot{V}_2 = -Cr^2 - \delta r + fr + \tilde{W}^T F_w^{-1} \dot{\tilde{W}} = -Cr^2 - \delta r + (\tilde{f} + \hat{f} + \varepsilon) r + \tilde{W}^T F_w^{-1} \dot{\tilde{W}} \tag{20}$$

$$= -Cr^2 - (\delta - \hat{f} - \varepsilon) r + \tilde{W}^T (F_w^{-1} \dot{\tilde{W}} + Hr)$$

Take $\dot{\tilde{W}} = -F_W Hr$, that neural network adaptive law is

$$\dot{\hat{W}} = F_W Hr \tag{21}$$

The actual controller input is

$$\delta = \hat{f} + k_2 r - v \tag{22}$$

where, v is used to overcome the robustness of neural network approximation error ε.

$$\dot{V}_1 = -Cr^2 - (\hat{f} + k_2 r - v) r + fr = -(C + k_2) r^2 + (\tilde{f} + \varepsilon + v) r \tag{23}$$

The robust item v is designed

$$v = -\varepsilon_N \operatorname{sgn}(r) \tag{24}$$

where, $\left\| \varepsilon \right\| \le \varepsilon_N$.

$$\dot{V}_2 = -Cr^2 - (\hat{f} + k_2 r - v - \hat{f} - \varepsilon) r = -(C + k_2) r^2 + (\varepsilon + v) r \tag{25}$$

$$= -(C + k_2) r^2 + \varepsilon r - \varepsilon_N \operatorname{sgn}(r) r \le 0$$

The whole control system and control law is simple and easy to implement.

4. The Ship Course Control Simulation

4.1. Simulation Research Overview

PID controller is designed, the system block diagram as shown in Figure 2. If a given course ψ_d, practical course ψ, the control law of PID is

$$\delta = K_p e + K_d \dot{e} + K_i \int_0^t e d\tau \tag{26}$$

where, $e = \psi_d - \psi$, K_p, K_d, K_i are parameters of PID controller.

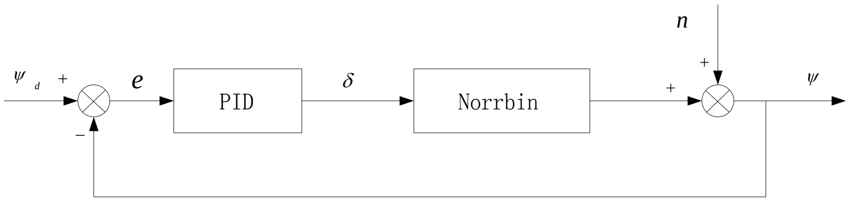


Figure 2. PID System Block Diagram

4.2. Simulation Results Of PID Controller

When $K_p = 2.5, K_d = 75, K_i = 0$, and the model without interference, PID control effect is ideal, response with no overshoot and adjustment time is about 80s, rudder Angle curve is relatively stable and smooth. The simulation results are shown in Figure 3, ψ_d is the given course, ψ is the actual course, δ is rudder Angle, $error$ is deviation.

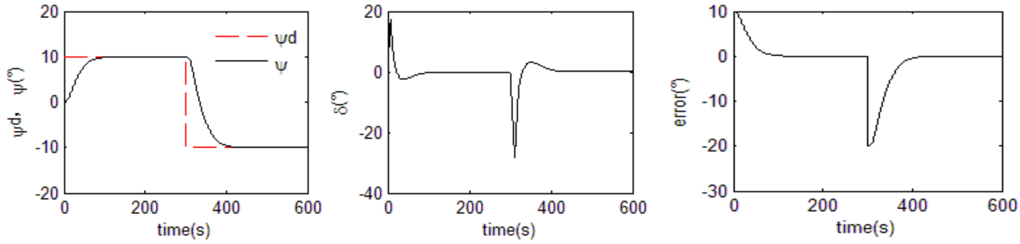


Figure 3. PID Simulation Results

4.3. Simulation Results of Backstepping Controller

Number of hidden layer neurons of RBF networks is $m = 7$, network structure is 5-7-1, take random value as network's initial weights, the initial value of the gaussian basis function are

$$C_j = \begin{bmatrix} -15 & -10 & -5 & 0 & 5 & 10 & 15 \\ -15 & -10 & -5 & 0 & 5 & 10 & 15 \\ -15 & -10 & -5 & 0 & 5 & 10 & 15 \\ -15 & -10 & -5 & 0 & 5 & 10 & 15 \\ -15 & -10 & -5 & 0 & 5 & 10 & 15 \end{bmatrix}^T, B = \begin{bmatrix} 40 & 40 & 40 & 40 & 40 \end{bmatrix}^T.$$

The network learning parameters are $\alpha = 0.6$, $\eta = 0.2$. Controller parameters are $k_1 = 0.03, k_2 = 50, \varepsilon_N = 0.001$. The simulation results are shown in Figure 4. The adjust time is about 90 s, rudder Angle curve is smooth, control results are ideal.

In the absence of disturbance and certain model parameters, the control effects of two kinds of controller are almost same.

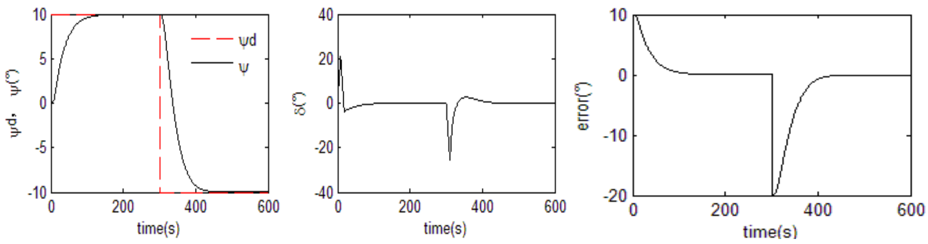
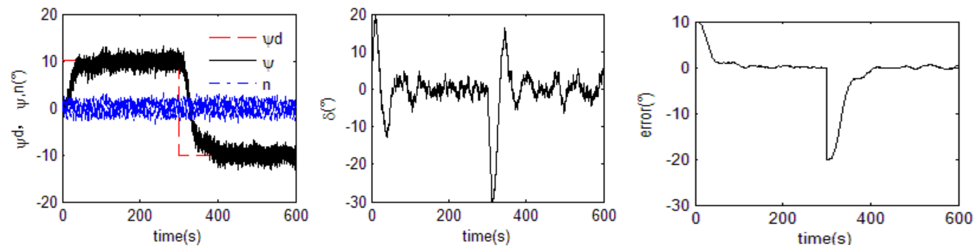


Figure 4. Simulation Results of Backstepping Control

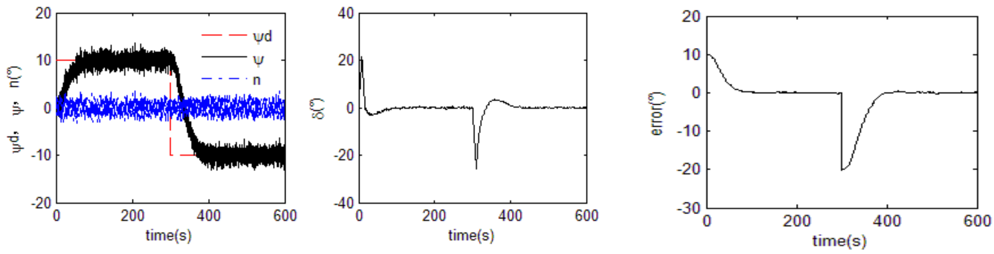
4.4. Joining Interference

Considered noise signal of the ship measured part, a standard variance 1 and zero mean white noise is taken, and the noise signal and the actual course are added together, on the feedback to join the first-order low-pass filter $Q(s) = 1/(6s+1)$.

The simulation results are shown in Figure 5. The simulation results show that after adding interference, the PID control system response curves and the rudder Angle curve volatility. And the influence of the backstepping control system basic without interference, the system has good robustness.



(a) PID



(B) Backstepping

Figure 5. Simulation Results Comparison

The simulation results show that after adding interference, the PID control system response curves and the rudder Angle curve volatility. And the influence of the backstepping control system basic without interference, the system has good robustness.

4.5. Model Parameters Changing

When the four parameters of ship model are changing, two controllers control effects are good, rudder angle curve is smooth, heading angle response curve without shock. As shown in Figure 6 (model parameters are two times).

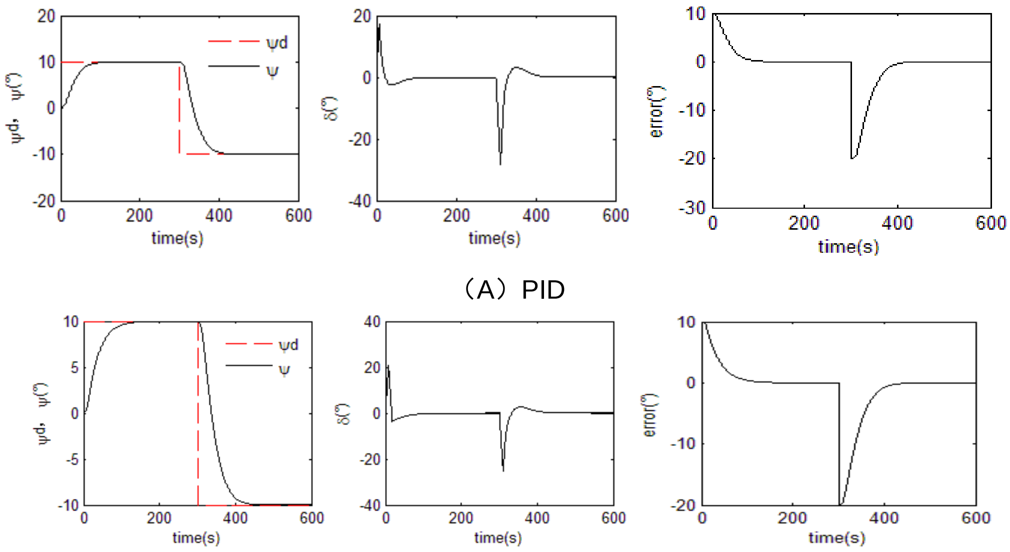


Figure 6. Simulation Results Comparision

5. Conclusion

In this paper, the main research work and achievements summarized as follows: Norrbin nonlinear model is chosen as the control object; study the principle and implementation of the RBF neural network approximation nonlinear model, approximation effect is good, can be used for real-time online identification system; RBF neural network to identify nonlinear ship model is used to design the adaptive backstepping controller, and considering the influence of model uncertainty and disturbance. Finally comparing with PID controller of control results, the simulation results show that the designed controller is effective.

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