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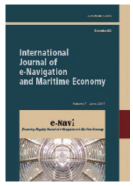

Original article

Design of Course-Keeping Controller for a Ship Based on Backstepping and Neural Networks☆

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Abstract

Due to the existence of uncertainties and the unknown time variant environmental disturbances for ship course nonlinear control system, the ship course adaptive neural network robust course-keeping controller is designed by combining the backstepping technique. The neural networks (NNs) are employed for the compensating of the nonlinear term of the nonlinear ship course-keeping control system. The designed adaptive laws are designed to estimate the weights of NNs and the bounds of unknown environmental disturbances. The first order commander are introduced to solve the problem of repeating differential operations in the traditional backstepping design method, which let the designed controller easier to implement in navigation practice and structure simplicity. Theoretically, it indicates that the proposed controller can track the setting course in arbitrary expected accuracy, while keeping all control signals in the ship course control closed-loop system are uniformly ultimately bounded. Finally, the training ship of Dalian Maritime University is taken for example; simulation results illustrated the effectiveness and the robustness of the proposed controller.

Keywords: Ship course control; DSC; Backstepping; Adaptive neural network

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1. Introduction

Ship motion control is an important research field in traffic engineering. Its ultimate goal is to improve the level of automation and intelligence, and ensure the safety, economy and comfort of the navigation (Zhang, 2012). Ship motion has the characteristics of nonlinear, strong coupling and large inertia, and it is a kind of typical uncertain nonlinear system (Jia and Yang, 1999).

Ship course control research has become an important direction in the field of ship motion control. At first, the PID controller is widely adopted (Xia, 1993). However, due to the poor robustness of PID to the external environment, PID cannot show its unique advantages. With the development of adaptive control theory, various control strategies were used in the course control. Nomoto model was used as the model of the ship motion control system in Yang, Yu and Jia (1999). The method of designing the robust PID-type autopilot was presented by using the Lyapunov stability theory. According to the characteristics of nonlinear and ship operation control in the process of complex interference, Liu, Wu and Zou (2000) designed a fuzzy and integral controller for ship course. The controller can realize the ship course keeping in case of disturbances. Considering the characteristics of the rudder in the ship course control system, Wu and Zhu (2009) presented the backstepping sliding mode design algorithm using state vector linearization of feedback linearization theory. And it designed a ship course-keeping backstepping controller. In the literature (Liu, Wu and Zou, 2000; Wu and Zhu, 2009), the control algorithms were designed based on the linear model of ship. However the nonlinearity of the ship model was ignored. Based on the Norbin nonlinear ship model, the nonlinear heading controller was designed in paper (Wu, Jia and Zhang, 2002) by using the backstepping method, and the simulation results showed that the method could achieve a better course keeping effect. The control strategy based on RBF neural network and backstepping was designed for ship course nonlinear control system in paper (Xia and Luan, 2015). Finally, the control designing strategies were used in the ship's course keeping control system. Considering the characteristics of the rudder, Wang, Liu and Li (2016) proposed an adaptive control design method based on the neural network and applied to the control of the ship course. It is difficult to eliminate the practical problems of the output energy and nonlinear part existing in backstepping method, and in the literature (Zhang, Zhang and Chen, 2015), the linear weakening of backstepping was presented and "Yulong" ship was taken as an example to simulate the ship course keeping. The results showed that the method is effective. In practice, the unknown time varying ocean environment of the ship was not considered in the literature (Zhang, Zhang and Chen, 2015). In order to overcome the uncertainty constant interference problem existing in the ship system, Guan, Zhang and Wang (2009) put forward a design scheme of ship course controller using closed-loop gain shaping algorithm and integral backstepping method. The simulation results showed that the designed controller can eliminate the static error caused by the sea wind, and have a better ship course control effect. According to the wave environment disturbance existing in ship course control system, Liu, Sui and Xiao, et al (2011) used a disturbance observer to estimate the disturbance of the environment, and combined with the backstepping sliding mode to design the keeping controller. The simulation results showed the effectiveness of the control strategy. For the effective stabilization of drift uncertainty in nonlinear ship course keeping system, Tian and Liu (2015) combined the Lyapunov energy function with the preset stabilization boundary with adaptive backtsepping method, and finally constructed the robust control with preset stabilization boundary. Although the disturbance influence of the external environment was considered, the uncertainty of ship model was ignored. Li, Bai and Xiao (2014) designed a new type of ship course sliding mode controller combined extended state observer with sliding mode technology for the nonlinear ship motion mathematical model. While the model of uncertainty and external disturbance were considered, but with the controller appears obvious chattering, and this will not be conducive to the rudder control of the implementation for the directive.

Li, Bai and Xiao (2014) constructed the Lyapunov function in backstepping method. It is favored by researchers for its systematic advantage of design process. However, the repeated derivation of the virtual control law in the backstepping design increased the complexity of the controller. The derivation of the virtual control law cannot be obtained when considering model uncertainty. In order to solve the problem of repeated derivation virtual control law in the traditional backstepping, Farrell, Polycarpou, and Sharma et al (2009) and Dong, Farrell and Polycarpou, et al (2012) introduced command filtering into backstepping method and proposed a filtering backstepping method. In addition, when the nonlinear mathematical model of the system is highly nonlinear, the application of backstepping is limited.

Inspired by the above literature, this paper proposes an adaptive neural network control method based on the instruction filtering technique for the nonlinear mathematical model of ship course motion. The method uses neural networks to approximate the unknown nonlinear of ship course mathematical model online. Using a two order filter to obtain the derivation of the virtual control law significantly simplifies the design process of backstepping method, and avoids the "computation explosion" problem. Considering unknown time-varying environment disturbance, an adaptive law is designed to estimate the unknown time-varying disturbance of the environment. Then the controller output of the equivalent rudder angle counteracts the environmental disturbance, and makes the actual output of the ship to track the desired course.

Symbol Description：R^n the n-dimensional Euclidean space, $\|\cdot\|$ is norm of Euclidean, $\lambda_{\max}(\cdot)$ and $\lambda_{\min}(\cdot)$ respectively represent the maximum and minimum values of the matrix, *diag*(•) is a diagonal matrix, $|\cdot|$ is absolute value.

2. Problem description and preliminary knowledge

2.1 Problem description

The relationship between rudder angle and course in the mathematical model of nonlinear ship course control system can be described as (Fossen, 1994):

$$\ddot{\psi} + \frac{1}{T}H(\dot{\psi}) = \frac{K}{T}\delta + d(t) \quad (1)$$

where T and K is ship manoeuvrability index; δ is the rudder angle, ψ is the heading angle, $d(t)$ is external environment disturbance, $H(\dot{\psi})$ is a nonlinear function related to $\dot{\psi}$, it can be approximated as

$$H(\dot{\psi}) = \alpha\dot{\psi} + \beta\dot{\psi}^3 \quad (2)$$

where α, β are nonlinear parameters of ship.

Let $x_1 = \psi$, $x_2 = \dot{\psi}$, $u = \delta$, and from the formula (1) and (2) we can obtain

$$\dot{x}_1 = x_2 \quad (3)$$

$$\dot{x}_2 = f(x_2) + \frac{K}{T}u + d(t) \quad (4)$$

$$y = x_1 \quad (5)$$

where $y \in R$ is the output of the system , $f(x_2) = -\frac{1}{T}H(x_2)$ is the unknown nonlinear function of the system, $H(x_2) = \alpha x_2 + \beta x_2^3$, u is the designed control law.

Assumption 1. $d(t)$ is a bounded external environment disturbance

$$|d(t)| \le \bar{d} \quad (6)$$

where $\bar{d}$ is the upper bound of external environment disturbance.

Assumption 2. Expected reference course y_d is smooth and bounded, and has two order continuous bounded derivative. There exists a positive constant B having $\Pi = \{(y_d, \dot{y}_d, \ddot{y}_d) : y_d^2 + \dot{y}_d^2 + \ddot{y}_d^2 \le B\}$.

2.2 RBF Neural Networks

In this paper, we use the radial basis function neural networks to approximate the unknown nonlinear terms in the mathematical model (1) of the nonlinear ship course control system. According to the paper (Wang X2016), it can be expressed as

$$H(Z) = \theta^{*T}S(Z) + E(Z) \quad (7)$$

where $H(Z)$ is the unknown nonlinear term to be approximated, Z is the input vector, θ^* is a ideal weight, $E(Z)$ is the approximation error having

$$|E(Z)| \le E^* \quad (8)$$

where E^* is the bound of the approximation error. $S(Z)$ is the radial basis function vector of neural networks, can be expressed as

$$S(Z)=\exp\left[-\frac{(Z-\mu_i)^T(Z-\mu_i)}{2\eta_i^2}\right] \tag{9}$$

where μ_i is center value， η_i is the width of the Gauss function.

Considering the ship unknown time-varying environment disturbance of the system of nonlinear ship course control, the control goal of this paper is using the instruction filtering technique and backstepping method to design a neural network adaptive course tracking controller and make the actual output to track the desired course direction.

3. Controller Design and Stability Analysis

In this part, aiming at the nonlinear ship course control (1), the external environment disturbance will be considered. Command filter technology and backstepping are used to design course tracking controller. The stability analysis of the closed-loop control system and the design process are given below.

Step 1：Define tracking error as

$$z_1 = y - y_d \tag{10}$$

where y is the actual output of the system, y_d is expected reference course.

Define compensated tracking error as

$$\bar{z}_1 = z_1 - s_1 \tag{11}$$

Get the derivative of the equation (11)

$$\dot{\bar{z}}_1 = x_2 - \dot{y}_d - \dot{s}_1 \tag{12}$$

Define tracking error

$$z_2 = x_2 - a_2 \tag{13}$$

Let a_2^0 get through the first order low pass filter with the time constant $e_2 > 0$, obtain filter virtual controller a_2

$$e_2\dot{a}_2 + a_2 = a_2^0 \tag{14}$$

where a_2^0 is the input of virtue control of the system.

Choose

$$\dot{s}_1 = -k_1 s_1 + a_2 - a_2^0 \tag{15}$$

where $k_1 > 0$ is a design parameter.

Take the equation (13) and (15) into equation (12), and have

$$\dot{\bar{z}}_1 = z_2 - \dot{y}_d + k_1 s_1 + a_2^0 \tag{16}$$

Define compensated tracking error as

$$\bar{z}_2 = z_2 - s_2 \tag{17}$$

The virtual control law is chosen as

$$a_2^0 = -k_1 z_1 - s_2 + \dot{y}_d \tag{18}$$

Take the equation (17) and (18) into equation (16), and have

$$\dot{\bar{z}}_1 = -k_1\bar{z}_1 + \bar{z}_2 \tag{19}$$

Choose pre-selection Lyapunov function as

$$V_1 = \frac{1}{2}\bar{z}_1^{\ 2} \tag{20}$$

Put equation (19) into derivation of (20)

$$\dot{V}_1 = \bar{z}_1\dot{\bar{z}}_1 = -k_1\bar{z}_1^{\ 2} + \bar{z}_1\bar{z}_2 \tag{21}$$

Step 2：Put equation(13) and (4) into derivation of (20) and get

$$\dot{\bar{z}}_2 = f(x_2) + \frac{K}{T}u + d - \dot{a}_2 - \dot{s}_2 \tag{22}$$

Choose

$$\dot{s}_2 = -k_2 s_2 \tag{23}$$

where $k_2 > 0$ is a designed parameter.

Take equation(23)into equation(22), and have

$$\dot{\bar{z}}_2 = f(x_2) + \frac{K}{T}u + d - \dot{a}_2 + k_2 s_2 \tag{24}$$

Choose Lyapunov function as

$$V_2 = V_1 + \frac{1}{2}\bar{z}_2^{\ 2} \tag{25}$$

Take equation(21) and(24) into the derivation of equation(25), and have

$$\dot{V}_2 = \dot{V}_1 + \bar{z}_2\dot{\bar{z}}_2$$

$$= -k_1\bar{z}_1^{\ 2} + \bar{z}_1\bar{z}_2 + \bar{z}_2\left[f(x_2) + \frac{K}{T}u + d - \dot{a}_2 + k_2 s_2\right] \tag{26}$$

where $f(x_2)$ is an unknown nonlinear function of the system, it cannot be directly used for the controller design. $f(x_2)$ has to be approximated by using RBF neural networks. d is completely unknown external disturbance, and the adaptive law is designed to adapt to the upper bound of disturbance.

$$f(x_2) = \theta^{*T} S(Z) + E(Z) \tag{27}$$

where $Z = x_2$ is input of RBF neural networks, $S(Z)$ is RBF neural networks vector, $E(Z)$ is approximation error. According to equation（26）and（27）, design control law and adaptive law as

$$u = \frac{T}{K}\left[-k_2 z_2 + \dot{a}_2 - \hat{d}\tanh(\frac{\bar{z}_2}{\varepsilon}) - \bar{z}_1 - \hat{\theta}^T S(Z)\right] \tag{28}$$

Now it is time to conduct the update laws for $\hat{d}$ and $\hat{\theta}$.

$$\dot{\hat{\theta}} = r\bar{z}_2 S(Z) - k_3\hat{\theta} \tag{29}$$

$$\dot{\hat{d}} = \rho\bar{z}_2 \tanh(\frac{\bar{z}_2}{\varepsilon}) - k_4\hat{d} \tag{30}$$

where $\tilde{\theta} = \theta^* - \hat{\theta}$ is error vector of estimation weight, $\hat{\theta}$ is ideal estimation θ^* is estimation, $\tilde{d} = \bar{d} - \hat{d}$, $\hat{d}$ is estimation of $\bar{d}$, $k_3 > 0, k_4 > 0$ are designed parameters.

According to (26)，construct the augmented Lyapunov function as

$$V_{2a} = V_2 + \frac{1}{2r}\tilde{\theta}^T\tilde{\theta} + \frac{1}{2\rho}\tilde{d}^2 \tag{31}$$

where $r > 0, \rho > 0$ are designed parameters.

Get the derivation of the augmented Lyapunov function

$$\dot{V}_{2a} = \dot{V}_2 + \frac{1}{r}\tilde{\theta}^T\dot{\tilde{\theta}} + \frac{1}{\rho}\tilde{d}\dot{\tilde{d}}$$

$$= -k_1\bar{z}_1^{\,2} + \bar{z}_1\bar{z}_2 + \bar{z}_2\left[f(x_2) + \frac{K}{T}u + d - \dot{a}_2 + k_2 s_2\right]$$

$$-\frac{1}{r}\tilde{\theta}^T\dot{\hat{\theta}} - \frac{1}{\rho}\tilde{d}\dot{\hat{d}} \tag{32}$$

Take equation (38)-(30) into equation(32), and obtain

$$\dot{V}_{2a} = -k_1\bar{z}_1^{\,2} - k_2\bar{z}_2^{\,2} + \bar{z}_2 E(Z) - \bar{z}_2\hat{d}\tanh(\frac{\bar{z}_2}{\varepsilon})$$

$$+\bar{z}_2 d + \frac{k_3}{r}\tilde{\theta}^T\hat{\theta} - \bar{z}_2\tilde{d}\tanh(\frac{\bar{z}_2}{\varepsilon}) + \frac{k_4}{\rho}\tilde{d}(\bar{d} - \tilde{d}) \tag{33}$$

According to Young's inequality, we get

$$\bar{z}_2 E(Z) \le \frac{1}{2}\bar{z}_2^2 + \frac{1}{2}E^{*2} \tag{34}$$

$$\frac{k_3}{r}\tilde{\theta}^T\hat{\theta} \le -\frac{k_3}{2r}\tilde{\theta}^T\tilde{\theta} + \frac{k_3}{2r}\theta^{*T}\theta^* \le -\frac{k_3}{2r}\tilde{\theta}^T\hat{\theta} + \frac{k_3}{2r}\theta_M^2 \tag{35}$$

$$\tilde{d}\bar{d} \le \frac{1}{2}\tilde{d}^2 + \frac{1}{2}\bar{d}^2 \tag{36}$$

where θ_M is the bound of ideal estimation θ^*.

According to equation(34)-(36) and (6) , equation(33)can be written as

$$\dot{V}_{2a} \le -k_1\bar{z}_1^{\,2} - \left(k_2 - \frac{1}{2}\right)\bar{z}_2^{\,2} + \frac{1}{2}E^{*2}$$

$$+\left[|\bar{z}_2| - \bar{z}_2\tanh(\frac{\bar{z}_2}{\varepsilon})\right]\bar{d} - \frac{k_3}{2r}\tilde{\theta}^2 + \frac{k_3}{2r}\theta_M^2$$

$$-\frac{k_4}{2\rho}\tilde{d}^2 + \frac{k_4}{2\rho}\bar{d}^2 \tag{37}$$

The characteristic of hyperbolic tangent function: For $\varepsilon > 0$, $a \in R$, have

$$0 \le |a| - a\tanh(\frac{a}{\varepsilon}) \le \beta\varepsilon \tag{38}$$

where a constant β meeting $\beta = e^{-(\beta+1)}$ is $\beta = 0.2785$.

Considering equation (38)，equation (37) is turned into

$$\dot{V}_{2a} \le -k_1\bar{z}_1^{\,2} - \left(k_2 - \frac{1}{2}\right)\bar{z}_2^{\,2} - \frac{k_3}{2r}\tilde{\theta}^T\tilde{\theta} - \frac{k_4}{2\rho}\tilde{d}^2 + \frac{1}{2}E^{*2}$$

$$+0.2785\varepsilon\bar{d} + \frac{k_3}{2r}\theta_M^2 + \frac{k_4}{2\rho}\bar{d}^2$$

$$\le -\mu V_{2a} + C \tag{39}$$

where $\mu = \min\left\{2k_1, 2\left(k_2 - \frac{1}{2}\right), k_3, k_4\right\}, C = \frac{1}{2}E^{*2}$

$+0.2785\varepsilon\bar{d}+\frac{k_3}{2r}\theta_M^2+\frac{k_4}{2\rho}\bar{d}^2$, and the designed parameters k_1, k_2, k_3, k_4 meet the following conditions.

$$\begin{cases} k_1 > 0 \\ k_2 > \frac{1}{2} \\ k_3 > 0 \\ k_4 > 0 \end{cases} \quad (40)$$

Obtain from equation(36)

$$0 \le V_{2a} \le \frac{C}{\mu} + [V_{2a}(0) - \frac{C}{\mu}]e^{-\mu t} \quad (41)$$

So that, when $t \to \infty$, V_{2a} converges to $\frac{C}{\mu}$, all the signals in the closed-loop system are bounded(Li J. F, 2013). If properly select the design parameters k_1, k_2, k_3, k_4, r, ρ, e_2, it Can make the course tracking error arbitrarily small.

4. Simulation Study

In order to verify the effectiveness of the designed controller, take Dalian Maritime University ocean training "Yulong" ship as an example for simulation. The ship parameters as below: Length between perpendiculars (L) is 126m, Breadth (moulded) (B) is 20.8m, load draught is 8.0m, square coefficient is 0.681, speed is 7.72m/s. By these parameters, the mathematical model parameters of ship nonlinear motion can be calculated $K = 0.478$, $T = 216$, $\alpha = 1$, $\beta = 30$. When selecting the desired course signal; a mathematical model representing the actual performance requirements is selected. (Li and Li, 2013)

$$\ddot{\psi}_m(t) + 0.19\dot{\psi}_m(t) + 0.015\psi_m(t) = 0.015\psi_r(t) \quad (42)$$

where ψ_m is ideal system performance of ship course, ψ_r is input command signal.

In the simulation, Initial conditions are selected as $x_1 = 10^\circ$, $x_2 = 0$, we choose Neural Networks $\theta^{*T}S(Z)$ containing 25 nodes, where center μ_l evenly distributed in $[-10, 10]$, width is $\eta_l = 4(l = 1, \ldots l_1)$, initial weight is $\hat{\theta} = 0$. The controller designed parameters are chosen as $k_1 = 1.82$, $k_2 = 3.21$, $k_3 = 2$, $k_4 = 2$, $r = 5$, $\rho = 3.495$, $\varepsilon = 0.01$.

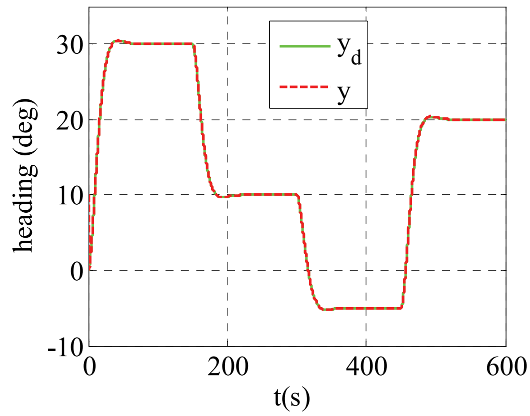

Figure 1: Course of ship

In figures of the simulation, Fig. 1 is the course of the ship, we can see from the figure that the design of the ship course tracking controller has a faster response speed and better tracking ability; Fig. 2 is the course tracking error of ship. It can be seen that the error is almost zero in the tracking process which indicates that the keeping effect is better.

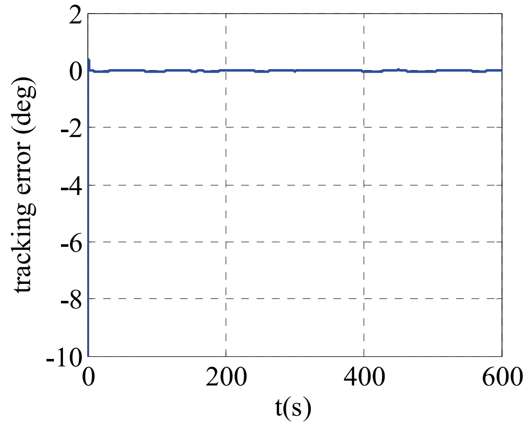

Figure 2: Course-keeping error of ship

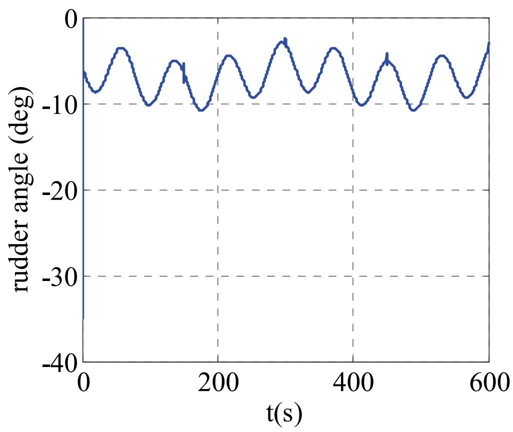

Figure 3: Rudder angular of ship

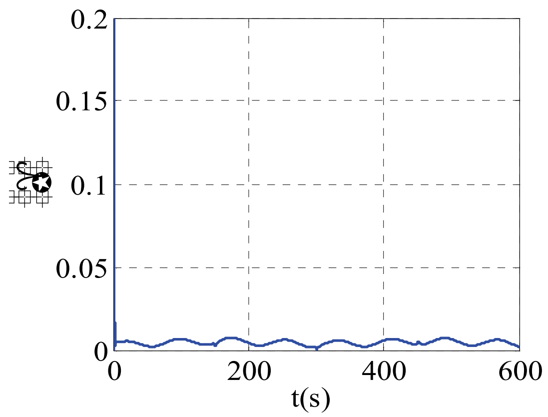

Figure 4: Norm of Neural Networks weight vector

Fig. 3 shows that the rudder angle of the ship is reasonable; the trajectory of estimation of the norm of NN ideal weight vector is shown in Fig. 4. The simulation results verify the effectiveness of the design of the course tracking controller based on the instruction filtering technique.

5. Conclusions

A ship course-keeping controller is designed based on the commander filtering technique and the backstepping method using neural network to approximate the nonlinear ship course control system. The adaptive law is designed for the complete unknown time-varying disturbance of the ship. The method has the advantages of using instruction filtering technology to avoid the explosion "problem" in the traditional backstepping method; Neural Network is utilized to approximate nonlinear terms in the ship model. It overcomes the problem of singular value of controller. Finally, simulation is carried out by MATLAB, and the effectiveness of the proposed control algorithm is verified.

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