RBF network based integral backstepping sliding mode control for USV

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Abstract. A kind of USV course RBF network control algorithm is put forward, which is on the basis of integral backstepping sliding mode. First of all, an integrator sliding surface were designed with the sliding mode variable structure control technology. Secondly, radial basis function neural network was applied to approximate the system nonlinear function and uncertain parameters. Furthermore, a nonlinear damping law was introduced to overcome the bounded outside interference. Finally, on the basis of the above, the system control law was deduced by using the backstepping method. The simulation results show that the neural network can accurately approximate the nonlinear function and uncertain parameters, and the controller output is smooth and the output is not sensitive to perturbation of parameters. Therefore, the proposed algorithm is effective for USV course control.

1 Introduction

Maritime shipping and production activities are becoming more and more busy, the Unmanned Surface Vehicle (USV) due to the advantages of high nautical rate, high efficiency, low cost, severe sea condition that can instead people to the various activities has become an important development trend of the future of the ship. Therefore, USV is playing increasing roles in commercial, scientific and military applications [1]. Due to the disturbances of wind, wave, current and other marine environment, the USV will inevitably deviate from the original given course when it is sailing. Precise course control is a prerequisite to solve the trajectory tracking, autonomous navigation and collision avoidance and other issues. The design of ship course controller is the issues of common concern for the control theory and control engineering [2].

With the development of computer technology and modern control theory, a variety of new control algorithms, such as the Lyapunov's direct method [3], backstepping control [4-6], sliding mode control [7-9], fuzzy control [10-12] and neural network control [13-16] have been applied to the research of ship course control. It is well known that the most advantage of sliding mode control is able to overcome uncertainty of the system, which has highly robustness for uncertain dynamic system with outside disturbance, especially effectiveness for control of modelless system. It is an important method for suppressing high frequency switching that causes chattering of control input. And the variable structure control system algorithm is simple, fast response, and robustness to external noise and parameter perturbation.

Therefore, it is useful for ship steering control. The integral link joined into the algorithm of sliding mode control can also effectively eliminate the bounded interference outside so that the original controller has a stronger anti-jamming capability.

In this paper, by taking the "Lanxin" USV of Dalian maritime university as the research object, aiming at its motion control system, the nonlinear mathematical model for the USV planar motion is established by the method of responsive integrated backstepping modeling. Based on the Nomoto mathematical model and the combination of integral backstepping control, sliding mode control and neural network control, a kind of USV course RBF network control algorithm of USV course control is proposed. With the disturbances of wind, wave and current, simulation results show that the designed course controller can be properly adopted to the "Lanxin" USV course keeping with good effectiveness.

2 Problem description

In actual voyages, ship movements usually exhibit a non-linear state. Therefore, in the mathematical model of USV plane motion, the nonlinear model is considered. Based on the linear mathematical model of plane three degrees of freedom, the nonlinear model is described by adding nonlinear term as following.

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

Where, K and T represent ship turning and follow index,

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φ represents ship course, δ represents rudder angle, $d(t)$ represents ship external interference. And $H(\dot{\varphi})$ is nonlinear function with regard to $\dot{\varphi}$, $H(\dot{\varphi}) = \alpha_1 \dot{\varphi} + \alpha_2 \dot{\varphi}^3 + \alpha_3 \dot{\varphi}^5 + \dots$, where, $\alpha_{i(i=1,2,3,\dots)}$ is the real value of the constant.

Make the following settings, $x_1 = \varphi$, $x_2 = \dot{\varphi}$, $u = \delta$. Then formula (1) can be converted into the following format:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x_2) + g \cdot u + d(t) \\ y = x_1 \end{cases} \quad (2)$$

Where, $f(x_2) = -\frac{1}{T} H(\dot{\varphi})$, $g = \frac{K}{T}$, x_1 and x_2 are system variable, y is the actual output of the system, $f(x_2)$ is unknown function of system, g is known gain of control input, $d(t)$ represents ship external interference, and u is the control input of system.

Based on above, the goal of this article is to seek control law u which is able to make the system output y asymptotically tracking expected course φ_r , the tracking error will be infinitely close to zero, that is $e = y - \varphi_r \rightarrow 0$, and the stabilization time will be reduced as much as possible.

3 Dteering control design based on backstepping

The design steps of the ship course controller contain the following steps.

Step 1. According to the characteristics of system (2), the following sliding surfaces are defined.

$$\begin{cases} \xi = z_2 \\ z_1 = x_1 - \varphi_r \\ z_2 = x_2 - \sigma_1 \end{cases} \quad (3)$$

Where, φ_r is the expected course, σ_1 is virtual stabilization, z_1 is the heading error. ξ is the integral term which can be able to eliminate the static error caused by the uncertain interference term in the control process.

Step 2. Lyapunov function is constructed to prove the asymptotic stability control system by using backstepping method. The first Lyapunov function is constructed.

$$V_1 = \frac{1}{2} z_1^2 \quad (4)$$

According to (3), it is obtained (5).

$$\dot{z}_1 = z_2 + \sigma_1 - \dot{\varphi}_r \quad (5)$$

It can be inferred formula (6) by formula (4).

$$\dot{V}_1 = z_1 \dot{z}_1 = z_1 [z_2 + \sigma_1 - \dot{\varphi}_r] \quad (6)$$

The virtual stabilization σ_1 is set as formula (7)

$$\sigma_1 = -k_1 z_1 + \dot{\varphi}_r \quad (7)$$

Therefore, it can be obtained (8).

$$\dot{\sigma}_1 = -k_1 (-k_1 z_1 + \dot{\varphi}_r) + \ddot{\varphi}_r \quad (8)$$

It can be obtained (9), according to (6) and (7).

$$\dot{V}_1 = -k_1 z_1^2 + z_1 z_2 \quad (9)$$

Similarly, it is obtained (10) according to (3).

$$\dot{z}_2 = \dot{x}_2 - \dot{\sigma}_1 = f(x_2) + g \cdot u + d(t) - \dot{\sigma}_1 \quad (10)$$

The second Lyapunov function is constructed.

$$V_2 = V_1 + \frac{1}{2} z_2^2 \quad (11)$$

It can be inferred formula (12) by formula (11).

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + z_2 \dot{z}_2 = -k_1 z_1^2 + z_1 z_2 \\ &+ z_2 (f(x_2) + g \cdot u + d(t) - \dot{\sigma}_1) \end{aligned} \quad (12)$$

And the third Lyapunov function is constructed.

$$V_3 = V_2 + \frac{\lambda}{2} \xi^2 \quad (13)$$

It can be inferred formula (14) by formula (13).

$$\begin{aligned} \dot{V}_3 &= \dot{V}_2 + \lambda \xi \dot{\xi} = -k_1 z_1^2 + z_1 z_2 + \lambda \xi z_2 \\ &+ z_2 (f(x_2) + g \cdot u + d(t) - \dot{\sigma}_1) \\ &= -k_1 z_1^2 + z_2 (z_1 + f(x_2) + g \cdot u + d(t) - \dot{\sigma}_1 + \lambda \xi) \end{aligned} \quad (14)$$

Step 3. The RBF network is used to adapt the system function $f(x)$, and its algorithm is (15).

$$\begin{cases} h_j = \exp\left(-\frac{\|x - c_j\|^2}{2b_j^2}\right), j=1,2,\dots,m \\ f(x) = W^* h(x) + \varepsilon \end{cases} \quad (15)$$

Where x is the network input, i represents one of the first input network input layer, j is a hidden layer of the network the first network input, $h = [h_j]^T$ is high

Gaussian function, $\mathbf{W}^*$ is the ideal for weighting value, ε is ideal for neural network approximation error.

$$\hat{f}(x_2) = \hat{\mathbf{W}}^T \mathbf{h}(\mathbf{x}) \quad (16)$$

Where, $\tilde{\mathbf{W}} = \hat{\mathbf{W}} - \mathbf{W}^*$.

The global Lyapunov function is constructed.

$$L = V_3 + \frac{1}{2} \gamma \tilde{\mathbf{W}}^T \tilde{\mathbf{W}} \quad (17)$$

It can be inferred formula (18) by formula (17).

$$\dot{L} = \dot{V}_3 + \gamma \tilde{\mathbf{W}}^T \dot{\tilde{\mathbf{W}}} \quad (18)$$

It can be obtained formula (19) by considering formula (14) and (16).

$$\begin{aligned} \dot{L} = & -k_1 \dot{z}_1^2 + \gamma \tilde{\mathbf{W}}^T \dot{\tilde{\mathbf{W}}} \\ & + z_2 \left[\dot{f}(x_2) + g \cdot u \right] \\ & + d'(t) - \dot{\sigma}_1 + \lambda \xi \end{aligned} \quad (19)$$

Step 4. In order to eliminate the uncertain interference term in equation (19), the nonlinear damping law[9] was designed.

$$u = \frac{1}{g} \left[-z_1 - \hat{f}(x_2) - (k_2 + \eta) z_2 - \lambda \xi + \dot{\sigma}_1 \right] \quad (20)$$

It can be inferred formula (21) by considering formula (19) and (20).

$$\begin{aligned} \dot{L} = & -k_1 \dot{z}_1^2 + \gamma \tilde{\mathbf{W}}^T \dot{\tilde{\mathbf{W}}} \\ & + z_2 \left[\dot{f}(x_2) - \hat{f}(x_2) + d'(t) - z_2 (k_2 + \eta) \right] \\ = & -k_1 \dot{z}_1^2 - k_2 z_2^2 - \eta z_2^2 + \tilde{\mathbf{W}}^T (\gamma \dot{\tilde{\mathbf{W}}} - \mathbf{h} z_2) \\ & + [d'(t) + \varepsilon] z_2 \end{aligned} \quad (21)$$

In order to ensure system asymptotically stable, the following adaptive law is designed.

$$\dot{\tilde{\mathbf{W}}} = \frac{1}{\gamma} \mathbf{h} z_2 \quad (22)$$

It is easy obtained formula (23) by theorem “ $x\dot{x} \leq \eta x^2 + \frac{1}{4\eta} \dot{x}^2$ ”.

$$\varpi z_2 \leq \eta z_2^2 + \frac{1}{4\eta} \|\varpi\|_\infty^2 \quad (23)$$

Where, $\varpi = d'(t) + \varepsilon$.

The fitness law of the network weights is still adopted formula (22), therefore, the formula (24) can be acquired.

$$\begin{aligned} \dot{L} = & -k_1 \dot{z}_1^2 - k_2 z_2^2 - \eta z_2^2 + \varpi z_2 \\ \leq & -k_1 \dot{z}_1^2 - k_2 z_2^2 + \frac{1}{4\eta} \|\varpi\|_\infty^2 \\ \leq & -k_2 z_2^2 + \frac{1}{4\eta} \|\varpi\|_\infty^2 \end{aligned} \quad (24)$$

In order to ensure that the system (2) is asymptotically stable, it is only need to prove the establishment which is $k_2 z_2^2 \geq \frac{1}{4\eta} \|\varpi\|_\infty^2$. Proof slightly, see the literature [4].

4 Simulation

USV course tracking control simulation is excuted by applying the above control algorithm.

4.1 Simulation Object and Conditions Setting

The establishment of USV planar motion mathematical model requires 8 known USV parameters, as shown in the table 1.

Table 1. The “LanXin” USV Parameters

Length Between Perpendiculars	7.02 m
Breadth	2.60 m
Speed	<=35 kn
Draft (full load)	0.32 m
Block Coefficient	0.6976
Displacement (full load)	2.73 m ³
Rudder Area	0.2091 m ²
Distance Between Barycenter and Center	0.35 m

In this paper, the planer motion mathematical model for the “Lanxin” USV adopts Nomoto model from the nonlinear mathematical model of formula (1).

There is the formula of matrix parameters of the mathematical model of the ship to calculate the above parameters, When the speed is 8.5kn, the gain constant and time constant are obtained through MATLAB programming, an $K=1.50226$, $T=0.90503$, $\alpha_1=0.001$, $\alpha_{i(i=2,3,\dots)}=0$. They are the Nomoto model parameters of the “Lanxin” USV [17]. In the actual simulation, the influence of wind and wave for USV motion is obtained with white noise and a second-order wave’s transfer function [18, 19]. The formula can be written as

$$y(s) = h(s) w(s) \quad (25)$$

Where $w(s)$ is the zero-mean Gaussian white noise, the power spectral density is 0.1, $h(s)$ is a second-order wave transfer function, and $h(s)$ can be written as formula (26).

$$\begin{cases} h(s) = \frac{K_\omega s}{s^2 + 2\xi\omega_0 s + \omega_0^2} \\ K_\omega = 2\xi\omega_0\sigma_m \end{cases} \quad (26).$$

Where ω_0 is the dominant frequency of sea waves, ξ is the damping coefficient, K_ω is the gain constant. σ_m is the constant describing wave intensity.

Based on USV motion model, the controller adds the model of the rudder servo system as formula (27).

$$\dot{\delta} = -\frac{1}{T_r}\delta + \frac{1}{T_r}\delta_r \quad (27).$$

Where T_r is time constant, for USV is generally about 0.2s. δ_r is Command rudder angle. There is the actually limit of rudder angle that is the formula (28).

$$|\delta| \leq 35^\circ \quad (28).$$

4.2 Simulation Results and Analysis

4.2.1 Course changes experiment

(1) experiment of 20° change of course

Protocol initial heading as 000°, expected course 020°, the simulation results without external interference and model parameter perturb are shown in Fig.1.

It can be seen from Figure 1, the control effect is good, and the output of course will reach the expected value faster, costing 30s without overshoot nearly; and rudder control horn is reasonable which can meet the characteristics requirements of steering system.

Fig.1. the output of course and rudder angle

(2) experiment of continuous change of course

Conduct experiment of tracking square wave, set the cycle as 100s, the change of course as 030°, the experimental results will be shown in Fig.2.

It can be seen from Figure 2, in the case of desired track changes, the new controller can do better in steering and easing the helm counter steering and output the right rudder angle according to ship characteristics and sea condition at the right time, and also conduct without overshoot in Fig 2.

Fig.2. the output of course and rudder angle when expected course continuous change

4.2.2 Interference experiment

(1) experiments of white noise interference

Protocol initial heading as 000°, desired track as 030°, apply amplitude as 0.1 white noise interference to course angle, the experiment results are shown in Fig.3.

Fig.3. the output of course and rudder angle under white noise interference

It can be seen from Figure 3, when the ship was disturbed by the outside world, the designed course controller will overcome outside interference to a certain degree, and will track the expected course with no shock of rudder controlling.

(2) experiments of ship parameter perturbation and white noise interference

Setting the protocol initial heading as 000°, desired track as 030°, propose maneuvering ship indices K、T perturb at 40%, apply amplitude as 0.1 and make white noise interference to the course, the experiment results are shown in Fig 4.

Fig.4. the output of course and rudder angle under model parameter perturb and white noise interference

It can be seen from Figure 4, when the ship model parameters occur perturbation with interference from the outside world, the course output from the new controller has smaller fluctuation around expected course, and has smaller shock amplitude of rudder controlling, thereby, it is illustrated that the anti-interference ability of the new controller is stronger.

5 Conclusion

An integral sliding mode controller with neural network was investigated for USV navigation, which realizes the accurate and stable tracking of the ship in the steering process, on the basis of backstepping method. With disturbances of wind, wave and current, the RBF network based integral backstepping sliding mode control system is simulated and the results of simulation show that the proposed algorithm is effective for USV course control.

Acknowledgment

This work was supported by the Foundation of Jiangsu Maritime Institute under Grant No.XR1501 and No.XR1504, and Jiangsu University Brand Professional Construction Project under Grant No. PPZY2015B177.

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