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Adaptive Neural Network Control for Ship Steering System Using Filtered Backstepping Design

[1]Junsheng Ren and [2]Lu Liu
[1]MOT (Ministry of Transportation) Key Laboratory of Marine Simulation and Control, Navigation College, Dalian Maritime University, 116026, Liaoning, P.R. China
[2]Department of Insurance, School of Finance, Dongbei University of Finance and Economics, 116020, Liaoning, P.R. China

Abstract: As regards ship course control, the ship is characterized by a nonlinear function with uncertainties, representing maneuvering characteristics. This study addresses the design of adaptive controller for ship steering system. The control objective is to drive the course to track a prescribed time-varying signal. We use filtered backstepping method to design the control law. Radial Basis Function (RBF) neural network learns the system's uncertainties and nonlinearities online. An adaptive law is combined with a control design including a filtered backstepping controller and RBF neural network approximator. Our analysis revealed even if there is no a priori knowledge about ship's system dynamics, the design can guarantee the ultimately uniformly boundedness for ship steering closed-loop system. Furthermore, the controller contains only one online learning parameter and the laborious differential computation in conventional ship method become unnecessary. Ship maneuvering scenario is simulated to verify the effectiveness of our approach.

Key words: Ship steering system, neural network, adaptive control, filtered backstepping

INTRODUCTION

Autopilot is important equipment for ship maneuvering. Its performance directly has great effect on ship safety and economics during voyage. However, ship dynamics are seriously influenced by ship type, speed, water depth, ballast condition, environmental disturbances and etc. Therefore, ship dynamic model's parameters have a high degree of uncertainties. Furthermore, ship motion is featured by its intrinsic nonlinearity. Nowadays, ship autopilots are usually designed by the algorithm of the PID (proportional-integral-derivative) controller in the framework of ship nominal model (Fossen, 2011). The main problems in PID controller arise from neglecting ship nonlinear dynamic characteristics and changes in ship motion parameters.

To address the issue of ship's uncertainties, several "robustifying" techniques have been developed: (i) adaptive method (Van Amerongen *et al*., 1975), where the controller parameters are tuned online based on simple linear model, (ii) robust methods where the upper bounds of the u n known parts are known beforehand and therefore, they often robust adaptive methods combine the merits of the above two schemes (Lauvdal and Fossen, 1998).

On the other research frontline, a class of recursive method, such as backstepping, forwarding and their combinations, has been applied to nonlinear control system. Adaptive backstepping is a powerful tool for the design of controllers for nonlinear systems in or transformable to the parameter strict-feedback form (Kanellakopoulos *et al*., 1991). Especially, backstepping approach has been used to design ship steering system. (Fossen and Strand, 1999) used nonlinear backstepping to exploit so-called good nonlinearities. (Du and Guo, 2004) combined adaptive backstepping algorithm with Nussbaum gain technique for ship course steering. However, these methods need iterative differentiation of certain nonlinear functions. Therefore, the designs therein are quite complicated.

In this paper, we investigate neural network for ship steering system. Neural networks are used to approximate the unknown nonlinearities and system uncertainties. By approximating the unknown system functions with neural networks, we will incorporate the filtered backstepping approach into the existing neural network based adaptive control design framework. This development will result in a systematic adaptive design method to lower the

Corresponding Author: Junsheng Ren, MOT (Ministry of Transportation) Key Laboratory of Marine Simulation and Control, Navigation College, Dalian Maritime University, 116026, Liaoning, P.R. China
Tel: 0086-0411-84729651 Fax: 0086-0411-84727742

complication of controller design in the existing method. Additionally, based on Lyapunov theory, we will present stability analysis. The analysis results reveal that, given any sufficiently smooth reference input, the proposed control law can be derived to guarantee the uniformly ultimate boundedness of the solution of the closed-loop system and make the tracking error arbitrarily small. The controller is much smaller than that constructed by using conventional backstepping approach. Finally, the ship steering controller is demonstrated by using Yulong ship.

THE MATHEMATICAL MODEL OF SHIP MOTION

Ship horizontal motion is defined in the relative coordinate system xop which is fixed to the ship. Ship position is described in earthed-fixed coordinate system $x_0o_oy_0$. The motion of the ship is shown in Fig. 1. ψ denotes ship course, r denotes ship's rate of turn, δ denotes rudder angle and G represents ship position of gravity center.

The control system discussed in this paper is designed for steering a ship on the given course. The controlled parameter is the ship course, ψ, while the controlling input parameter is the rudder angle, δ. The equations describing dynamic characteristics of the ship were derived from Newtonian dyanmics laws. Nomoto's first-order and second-order models have been used extensively by control engineers for analysis and design of ship autopilots.

For ship's linear model describing the relation between ship course and rudder angle, the rudder-angle should not exceed 5°. If the rudder angle exceeds 5°, the model will be unsuitable. Therefore, for the present study, the mathematical model of the dynamic characteristics of the ship is described by Norbin (Van Amerongen *et al*., 1975).

$$T\psi+H_{Non}(\psi) = K\delta \quad (1)$$

where, K and T are maneuverability indices, the other coefficients in (1) are constants and $H_{Non}(\psi)$ is a nonlinear function of ψ as follows:

$$H_{Non}(\psi) = a_3\psi^3+a_2\psi^2+a_1\psi+a_0 \quad (2)$$

where, a_0,a_1, a_2 and a_3 are the unknown coefficients. This model can be used for large rudder angles and course instability. These coefficients can be obtained from the spiral test for course-stable ships, while the reverse spiral test is used for course-unstable ships. In this paper, we assume that uncertain nonlinear part $H_{Non}(\psi)$ in (2) is completely unknown.

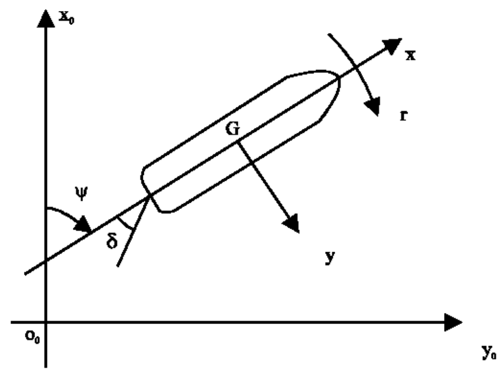

Fig. 1: Coordinate system

For the convenience, we introduce $x_1 = \psi$, $x_2 = \psi$ and $u = \delta$. Then, the Norrbin model can be rewritten into the following nonlinear system under the framework of strict-feedback form:

$$\begin{cases}\dot{x}_1 = x_2\\ \dot{x}_2 = f(x)+g(x)u\end{cases} \quad (3)$$

where $x = [x_1, x_2]^T$, $f(x) = H_{non}(\psi)/T$, f(x) denotes the system's unknown dynamics, g(x) = K/T.

In this paper, we will design ship's course-keeping adaptive controller for the uncertain nonlinear system in the strict-feedback form in (3). The proposed adaptive controller will guarantee ultimate uniform boundedness of the closed-loop system.

MATHEMATICAL MODEL OF SHIP MOTION

We exploit Radial Basis Function (RBF) neural network (Haykin, 1999) to provide the function approximation capabilities. RBF neural network performs the nonlinear mapping from input layer to hidden layer as shown in Fig. 2. A RBF network is made up of a collection of parallel processing units called nodes. The output of the ith node is defined by a Gaussian function:

$$s_i(x) = \exp\frac{(x-c_i)^2}{\sigma_i^2} \quad (5)$$

where, $x \in \Re^r$ is the input to the network, c_i is the center of the ith node and σ_i is its size of infiuence. The output of the neural network is y = f(x). It has been proven that RBF network can approximate any continuous function over a compact set (Haykin, 1999). Next, we will introduce a useful lemma for the controller design.

Lemma 1 (Yang and Wang, 2007) For any given real continuous function $f(x,\theta)$ with $f(0,\theta) = 0$ for $\forall\theta\in\Theta$, if the

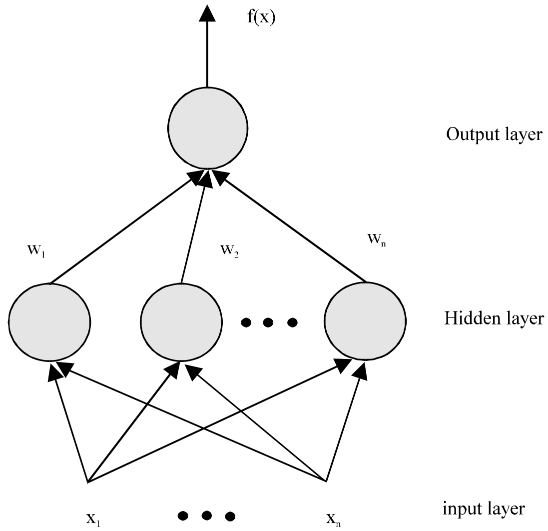

Fig. 2: Basic architecture of RBF neural network

continuous function separation technique and RBF neural network approximation technique are used, then f (x, θ) can be denoted as follows:

$$f(x,\theta) = \bar{s}(x)A_z x \quad (6)$$

where, $\bar{s}(x) = [1,s(x)] = [1,s_1(x), 1,s_2(x),....,1,s_l(x)]$ l are the RBFs which are known and l is the node number. $A_z^T = [\varepsilon, W^T]$, $\varepsilon^T = [\varepsilon_1, \varepsilon_2, \varepsilon_3,...,\varepsilon_n]$ is a vector of the approximation error and W is a weight matrix.

SHIP STEERING CONTROLLER DESIGN

In this study, the control objective is to steer ship course x_{1c} to track the output of the given time-varying signal and ensure the ultimate uniform boundedness for the signals in ship close-loop system. Design procedures of ship steering adaptive controller will be presented as follows:

Step 1: Define two tracking errors for the state x_{1c}:

$$\tilde{x}_1 = x_1 - x_{1c} \quad (7)$$

$$\bar{x}_1 = \tilde{x}_1 - \xi_1 \quad (8)$$

where, x_{1c} denotes the desired ship course, $\tilde{x}_1$ denotes the tracking error of ship course and $\bar{x}_1$ denotes the compensated tracking errors of ship course. In this paper, we assume that x_{1c} is continuous and has 1-order derivative:

$$\dot{\xi}_1 = -k_1\xi_1 + (x_{2c} - x_{2c}^0) \quad (9)$$

$$x_{2c}^0 = \alpha_1 - \xi_2 \quad (10)$$

where, ξ_2 will be defined in the step 2, x_{2c} and $\bar{x}_{2c}$ are obtained after the filtering of x_{2c}^0 and will discussed later, a_1 denotes virtual control input, $k_1>0$ is the constant to be chosen by the designer. Then, we obtain:

$$\dot{\bar{x}}_1 = \bar{x}_2 + \alpha_1 + k_1\xi_1 - \dot{x}_{1c} \quad (11)$$

Choose the following Lyapunov candidate function:

$$V_1(t) = \frac{1}{2}\bar{x}_1^2 \quad (12)$$

Then, the derivative of Lyapunov candidate function (12) is given by:

$$\dot{V}(t) = \bar{x}_1\bar{x}_2 + \bar{x}_1\alpha_1 + k_1\bar{x}_1\xi_1 + \bar{x}_1\dot{x}_{1c} \quad (13)$$

The virtual control input a_1 is formulated as follows:

$$\alpha_1 = -k_1\tilde{x}_1 - \dot{x}_{1c} \quad (14)$$

Substituting the virtual control input (22) into (21) will yield:

$$\dot{V}_1(t) = -c_1V_1(t) + \bar{x}_1\bar{x}_2 \quad (15)$$

where $c_1 = 2k_1$.

Step 2: Similar to Step 1, we define the following two tracking errors for x_2:

$$\tilde{x}_2 = x_2 - x_{2c} \quad (16)$$

$$\bar{x}_2 = \tilde{x}_2 - \xi_2 \quad (17)$$

where, $\tilde{x}_2$ denotes tracking error, ξ_2 will be defined in the subsequent descriptions, $\bar{x}_2$ denotes compensated tracking error. We use RBF neural network (6) to approximate the unknown dynamics f(x) in ship course control system (3). Then we obtain:

$$f(x) = \bar{S}(x)A_z\bar{x}_2 + \bar{S}(x)x_{2c} + \bar{S}(x)A_z\xi_2 \quad (18)$$

where, $\bar{S}(x)$ and A_z follows the definition in Section II. From (3) and (26), we obtain:

$$\begin{aligned}\dot{\bar{x}}_1 &= g(x)u + \bar{S}(x)A_z\bar{x}_2 + \bar{S}(x)x_{2c} \\ &+ \bar{S}(x)A_z\xi_2 - \dot{x}_{2c} \\ &= g(x)u + \bar{S}(x)A_z x + \Omega\end{aligned} \tag{19}$$

where, Ω is introduced for the reason of the convenience and:

$$\begin{aligned}\Omega &= A_z\bar{S}(x)x_{2c} + \bar{S}(x)A_z\xi_2 - \dot{x}_{2c} \\ &\le |c_\upsilon|\|Q_U\||x_{2c}| + |c_\upsilon|\|Q_U\|\bar{S}(x)|\xi_2| - \dot{x}_{2c} \\ &\le \chi^*\beta(x)\end{aligned} \tag{20}$$

where, $\|\bullet\|$ denotes the vector's Eulidean norm or matrix's induced 2-norm, $A_z = c_v Q_u$, $\|Q_u\| = 1$, c_2 is the unknown constant and only for the design use, whose accurate value is necessarily known:

$$\chi^* = \max\{|c_\upsilon|\|x_{2c}\|, |c_\upsilon|, |\dot{x}_{2c}|\}$$
$$\beta(x) = 1 + \|\bar{S}(x)\| + \|\bar{S}(x)\||\xi_2|$$

Next, we introduce the definition:

$$\dot{\xi}_2 = -k_2\xi_2 + g(x)(u_c - u_c^0) \tag{21}$$

where, $k_2>0$ is the constant to be chosen by the designer, u_c^0 denotes filtered to output u_c, $u_c = u$. Generally, we choose $u_c^0 = u_c = u$. Combining (16), (17), (20) and (21) yields:

$$\dot{\bar{x}}_2 = \bar{S}(x)Q_1\bar{x} + \Omega + g(x)u + k_2\xi_2 \tag{22}$$

We choose the following Lyapunov candidate function:

$$V_2(t) = V_1(t) + \frac{1}{2}\bar{x}_2^2 + \frac{1}{2}\Gamma^{-1}\tilde{\theta}^2 \tag{23}$$

where, $\tilde{\theta} = \theta^* - \hat{\theta}$ and $\hat{\theta}$ denote the estimated value of the adapted parameters θ^*, $\Gamma>0$ is a constant and chosen by the designer. The derivative of the Lyapunov candidate function is given by:

$$\begin{aligned}\dot{V}_2(t) \le \dot{V}_1(t) &+ \bar{x}_2\bar{S}(x)A_z\bar{x}_2 + \bar{x}_2\chi\beta(x) + \bar{x}_2 g(x)u \\ &+ \bar{x}_2k_2\xi_2 + \Gamma^{-1}\tilde{\theta}\dot{\hat{\theta}}\end{aligned} \tag{24}$$

The items $\bar{x}_2\bar{S}(x)A_z\bar{x}_2$ and $\bar{x}_2\chi\beta(x)$ in (24) are discussed as follows, respectively. By use of Young's inequality in Lemma 1, we obtain:

$$\begin{aligned}\bar{x}_2\bar{S}(x)A_z\bar{x}_2 + \bar{x}_2\chi^*\beta(x) &\le \frac{c_\upsilon^2}{2w}\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) \\ &+ \frac{w}{2}\bar{x}^TQ_U^TQ_U\bar{x} + \chi^*|\bar{x}_2||\beta(x)| \\ &\le \theta^*\frac{1}{2w}\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) + \theta^*|\bar{x}_2||\beta(x)| + \frac{w}{2}\bar{x}_2^T\bar{x}_2 \\ &\le \hat{\theta}\frac{1}{2w}\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) + \hat{\theta}|\bar{x}_2||\beta(x)| \\ &+ \frac{w}{2}\bar{x}_2^T\bar{x}_2 + \tilde{\theta}\frac{1}{2w}\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) + \tilde{\theta}|\bar{x}_2||\beta(x)|\end{aligned} \tag{25}$$

where, $\theta^* = \min\{c_v^2, \chi^*\}$ and $w>0$ is chosen by the designer. Then by use of the inequality in Lemma 2, we construct the following ship course-keeping steering controller:

$$u = \frac{1}{g(x)}\left[-k_2\bar{x}_2 - \frac{1}{2w}\hat{\theta}\bar{x}_2\bar{S}(x)\bar{S}^T(x) - \bar{x}_1 - \frac{\bar{x}_2\hat{\theta}^2\beta^2(x)}{|\bar{x}_2|\hat{\theta}\beta(x) + \varepsilon}\right] \tag{26}$$

and adaptive law:

$$\dot{\hat{\theta}} = \Gamma\left[\frac{1}{2w}\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) + |\bar{x}_2|\beta(x) - \sigma(\hat{\theta} - \theta_0)\right] \tag{27}$$

where, $\sigma>0$ and $\theta_0>0$ are constants and specified by the designer.

By completion of squares, we obtain:

$$2\tilde{\theta}(\hat{\theta} - \theta^0) \le -\tilde{\theta}^2 - (\hat{\theta} - \theta^0)^2 + (\theta^* - \theta^0)^2 \tag{28}$$

For the convenience, we introduce the following definition:

$$c_2 := \min\{2k_1 - w, 2k_2 - w, \Gamma\sigma\} \tag{29}$$

$$\varpi := \frac{\sigma}{2}(\theta^* - \theta^0)^2 + \varepsilon \tag{30}$$

Combining (25), (27)-(31) results in:

$$\dot{V}_2(t) \le -cV_2(t) + \varpi \tag{31}$$

From (32) and Lemma 3, we obtain:

$$V_2(t) \le V(t_0)\exp[-c(t - t_0)] + c/\varpi, \quad t \ge t_0 \tag{32}$$

Then we know $\bar{x}_i (i = 1,2)$, $\tilde{\theta}$ belong to the following compact sets:

$$\left\{(\bar{x}_i, \tilde{\theta}) \middle| V_2(t) \le V(0) + \frac{\varpi}{c}\right\} \tag{33}$$

This also indicates that $\bar{x}_I$, $\tilde{\theta}$ in the closed-loop system is ultimate uniform bounded. Next, we discuss the generation of signal x_{2c}. In this paper, x_{2c} generated by the prescribed filter. We employ a prefilter (Djapic *et al*., 2008) to avoid differentiate virtual control signal x_{ic}^0. The transfer function from input signal x_{ic}^0 to x_{ic} is given as follows:

$$\frac{x_{ic}(s)}{x_{ic}^0} = H(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{34}$$

where, ξ denotes damping ratio and ω_n denotes natural frequency. If the signal x_{ic}^0's bandwidth is lower than H(s), the error $x_{ic}^0(t)$-$x_i(t)$ will be quite small. Suppose that the signal x_{ic}^0's bandwidth is known, sufficient large natural frequency ω_n will make the above filter (34) produce x_c and $\bar{x}_c$ and guarantee that the error $\left|x_{ic}^0(t) - x_{ic}(t)\right|$ is small.

Furthermore, it can be concluded from (9) and (22) that $x_{ic} \rightarrow x_{ic}^0$ can be arbitrarily small through appropriate choice of the filter's parameters. Then, we obtain $\xi_i \rightarrow 0$ and $\bar{x}_I \rightarrow \tilde{x}_i$. Hence, course tracking error $\tilde{x}_i$ is UUB and may be arbitrarily small by reasonably choosing design parameters. From (18), the filter's output is also bounded. From the aforementioned, the control law (27) can ensure the UUB of all the signals in the closed-loop system.

SIMULATION STUDIES

This part will takes Dalian Maritime University's training ship "Yulong" as example. With software Simulink Toolbox in Matlab 7.2, simulation studies are carried out for the ship steering controller design. Training ship Yulong's main particulars are listed as follows: design speed 14 knots, length between main particulars 126 m, breadth 20.8 m, draft 8 m, cubic coefficient 0.681, buoyant center position 0.25 m, rudder area 18.8 m. From these parameters, K = 0.4343, T = 238.7592 in (1) could be calculated. The control objective is to drive the ship course x_1 to track a reference signal x_{1c}, which is the output of the following transfer function:

$$x_{1c}(t) = \frac{0.0025}{s^2 + 0.08s + 0.0025}\left[x_{1c,r}(t)\right] \tag{35}$$

where, input $x_{1r,c}(t)$ is square wave with period 1000 seconds and amplitude 20°. In the command filter, we choose the parameters ξ = 0.7 and ω_n = 2.5. We choose the virtual control input:

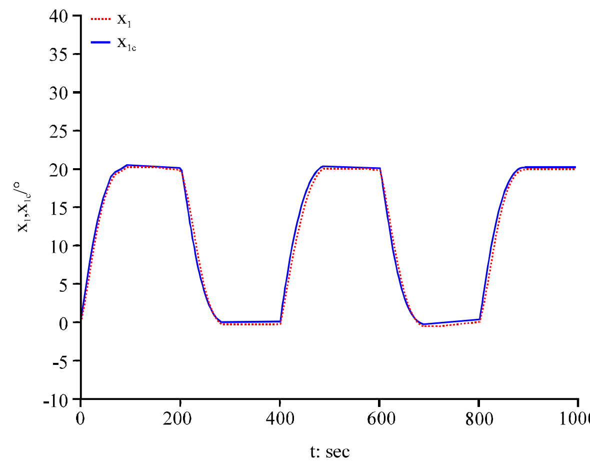

Fig. 3: Comparison of the state x_1 and the desired trajectory x_{ic}

$$\alpha_1 = -0.1\tilde{x}_1 - \dot{x}_{1c} \tag{36}$$

We choose the ship course's adaptive controller as follows:

$$u = \frac{T}{K}\left[-4\tilde{x}_2 - 20\hat{\theta}\bar{x}_2\bar{S}(x)\bar{S}^T(x) - \bar{x}_1 - \frac{\bar{x}_2\hat{\theta}^2\beta^2(x)}{|\bar{x}_2|\hat{\theta}\beta(x) + 0.5}\right] \tag{37}$$

equipped with adaptive laws:

$$\dot{\hat{\theta}} = 2\left[20\bar{x}_2^2\bar{S}(x)\bar{S}^T(x) + |\bar{x}_2|\beta(x) - 0.05(\hat{\theta} - 0.01)\right] \tag{38}$$

The selection of the centers and widths of RBF has a great influence on the performance of the designed controller. RBF networs for the controller (37) and adaptive law (38) contain 6 nodes, namely, l = 5, with center c_i evenly spaced in [-10,30]×[-10,30] and with η_i = 10 degrees.

During simulation experiment, we use separate-type model as platform, where hydrodynamic characteristics of hull, propeller and rudder are taken into consideration. Figure 3-7 illustrate the simulation results. Figure 3 shows the time response of actual course and desired trajectory, where real line represents actual course x_1 and dotted line denotes desired trajectory x_{1c}. Figure 2 gives the tracking error between x_1 and x_{1c}. Figure 3 and 4 shows that the controller performance is satisfactory.

Figure 3 is control input, or rudder angle. Figure 4 is adaptive parameter $\hat{\theta}$, respectively. Figure 4 presents the filter output in (48). From Fig. 3-7, It can be concluded that all the signals in the closed-loop system are UUB.

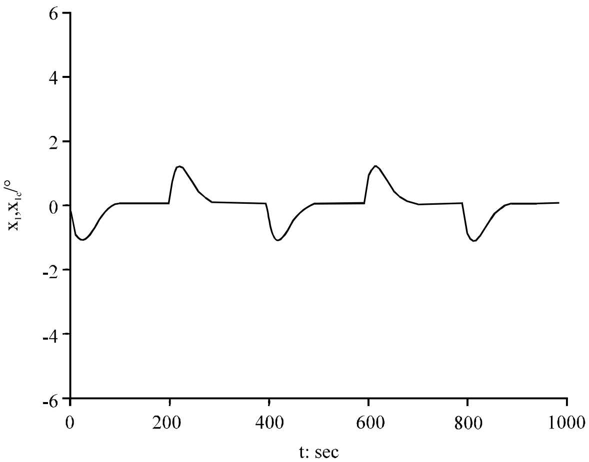

Fig. 4: Tracking error

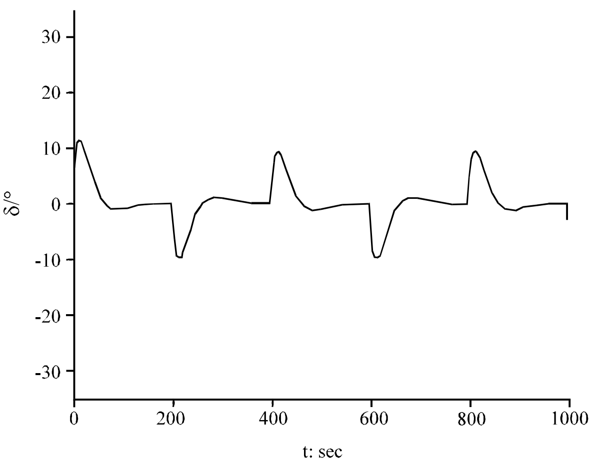

Fig. 5: Control input

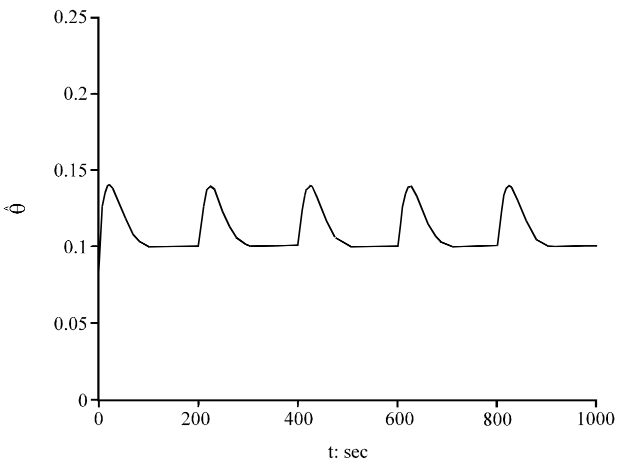

Fig. 6: Adaptive law: θ

Furthermore, fine tuning of the parameters k_1, k_2, Γ can achieve more precise tracking error, but with larger control input.

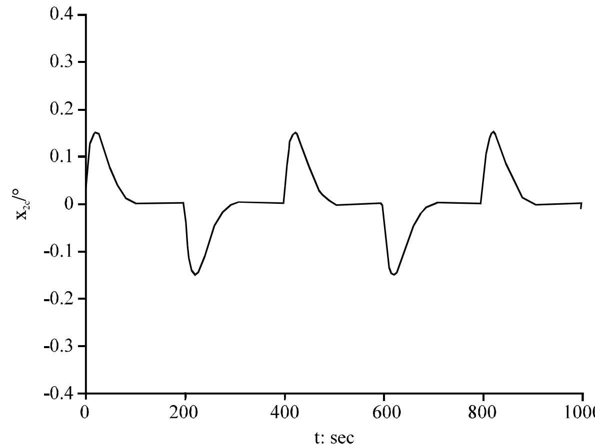

Fig. 7: Output of the filter

APPENDIX

Lemma 2 (Yang, 1999) For scalar time functions $x(t)\in\Re$ and $y(t)\in\Re$, it holds that:

$$2xy \le \frac{1}{\omega}x^2 + \omega y^2 \tag{40}$$

for any $\omega>0$.

Lemma 3 IF there exists:

$$u = \frac{AB^2}{|A|B + \varepsilon} \tag{41}$$

where, u is control input, $A,B\neq 0$, $A,B\in\Re$ and $\varepsilon>0$, then:

$$Au + |A|B \le \varepsilon \tag{42}$$

will always holds.

Proof: Substitute (42) into (41) and we have:

$$Au + |A|B \le \frac{|A|B\varepsilon}{|A|B + \varepsilon} \le \frac{|A|B\varepsilon + \varepsilon^2}{|A|B + \varepsilon} \le \varepsilon$$

Lemma 4 (Zhou *et al*., 2005) Let $V:[0,\infty)\to\Re$ satisfies the inequality:

$$\dot{V} \le -2a_0V + b_0, \quad t \ge 0, \tag{43}$$

where, a_0 and b_0 are positive constants. Then:

$$V(t) \le V(t_0)\exp[-2a_0(t - t_0)] + \frac{b_0}{2a_0} \tag{44}$$

CONCLUSIONS

Automatic ship steering system is an attractive research area. The system design needs taking the nonlinearity and uncertainties into account for ship performance. Our analysis demonstrates that the unknown parameters in Norrbin's ship model don't has damage on the stability of ship steering closed-loop system. We establish the boundedness of all signals in the system. Additionally, fitered backstepping approach reduces the computation load. The system response tracks the external reference signal satisfactorily. Our ship steering strategy is verified through simulation scenarios where the nonlinearity parameters are unknown. The presented adaptive course-keeping controller is simple. Therefore, the labor-saving computation efforts make the scheme interesting its practical implementation.

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