

Combined Neural Network and PD Adaptive Tracking Controller for Ship Steering System

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Abstract: *In this paper, a combined RBF neural network sliding mode control and PD adaptive tracking controller is proposed for controlling the directional heading course of a ship. Due to the high nonlinearity and uncertainty of the ship dynamics as well as the effect of wave disturbances a performance evaluation and ship controller design is stay difficult task. The Neural network used for adaptively learn the uncertain dynamics bounds of the ship and their output used as part of the control law moreover the PD term is used to reduce the effect of the approximation error inherited in the RBF networks. The stability of the system with the combined control law guaranteed through Lyapunov analysis. Numeric simulation results confirm the proposed controller provide good system stability and convergence.*

Index Terms— NEURAL NETWORK, ADAPTIVE CONTROL, SLIDING MODE CONTROL, MODEL REFERENCE PD CONTROLLER.

I. INTRODUCTION

An autopilot is a ship steering controller which is an important equipment for ship maneuvering, and automatically manipulates the rudder angle to reduce the error between the reference course or heading and actual course. The autopilot performance directly effect safety and fuel want consumption. Ship autopilot designed by conventional controller must be adjusted in accordance with the variation of ship dynamic and environmental disturbances where ship dynamic are greatly influences by ships speed, type ballast condition, so, the ship model has a high degree of nonlinearity and uncertainty, and this is beside the environmental effect namely the wind and currents [1, 2]. To address the major difficulties of the ship nonlinearity and uncertainty, several techniques have been developed, J. Van Ameronge [3] proposed adaptive model reference approach. Lavudal and Fossen [4] suggested robust adaptive autopilot with waves filter and integral action. Other researches, a class of recursive algorithms such as backstepping and filtered backstepping have been applied [5]. In [2] an adaptive neural network control for ship steering system is proposed and

backstepping techniques has been used. A fuzzy variable structure controller is designed based on exponential reaching law presented in [6]. While a model reference based neural network is used in [7]. In [8] J. R. Layne and K. Passino had proposed a fuzzy reference model learning control for steering cargo ship system.

In this Paper, a combined neural network and PD controller is proposed. The neural network is used to adaptively learning ship uncertainly bound, and the output is used as a parameter in the control law. To reduce the effect of the unknown dynamics of the ship; a PD term has been added to the control law. The PD term will compensate the model uncertainty outside the neural network state region, this provide global stability, moreover, the PD term handles the inherent network approximation error and this will improve the tracking. The asymptotical stability of the system including both terms of the control law the sliding and the PD terms has been approved using Lyapunov theorem beside the derivation of the learning algorithm of the neural networks.

$$L(s, \tilde{\Theta}) \leq \frac{1}{2}s^2 + \frac{1}{2}\Gamma_1^{-1} \|\tilde{\Theta}_1\|^2 + \frac{1}{2}\Gamma_2^{-1} \|\tilde{\Theta}_2\|^2 \quad (18)$$

Differentiating (16) w.r.t. time yields:

$$\begin{aligned} \dot{L}(s, \tilde{\Theta}) &= s \dot{s} - \Gamma_1^{-1} \tilde{\Theta}_1^T \dot{\tilde{\Theta}}_1 - \Gamma_2^{-1} \tilde{\Theta}_2^T \dot{\tilde{\Theta}}_2 \\ &= s \dot{s} - \Gamma_1^{-1} \tilde{\Theta}_1^T \dot{\tilde{\Theta}}_1 - \Gamma_2^{-1} \tilde{\Theta}_2^T \dot{\tilde{\Theta}}_2 \\ &= s [CAe + C(A - A_m)\mathbf{x}_m + CF \\ &\quad - CB_m\psi_r + CB \delta(t)] - \Gamma_1^{-1} \tilde{\Theta}_1^T \dot{\tilde{\Theta}}_1 \\ &\quad - \Gamma_2^{-1} \tilde{\Theta}_2^T \dot{\tilde{\Theta}}_2 \\ &= -s CB K_p s + s CAe + s C(A - \\ &\quad A_m)\mathbf{x}_m + s CF - s CB_m\psi_r - \\ &\quad s CB \frac{sgn(s)}{c_n} (\hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1))^2 [|CAe| + \\ &\quad |C(A - A_r)\mathbf{x}_m| + |CB_m\psi_r|] - \\ &\quad s CB sgn(s) (\hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1) \hat{\Phi}_2(\mathbf{x}|\hat{\Theta}_2)) - \\ &\quad \Gamma_1^{-1} \tilde{\Theta}_1^T \dot{\tilde{\Theta}}_1 - \Gamma_2^{-1} \tilde{\Theta}_2^T \dot{\tilde{\Theta}}_2 \end{aligned} \quad (19)$$

Assume that the learning laws defined as follow:

$$\dot{\hat{\Theta}}_1 = \Gamma_1 sgn(s) s \zeta_1(\mathbf{x}) [|CAe| + |C(A - A_m)\mathbf{x}_m| + |CB_m\psi_r|] \quad (20)$$

$$\dot{\hat{\Theta}}_2 = \Gamma_2 sgn(s) s c_n \zeta_2(\mathbf{x}) \quad (21)$$

Then (19) can be written as below:

$$\begin{aligned} \dot{L}(s, \tilde{\Theta}) &= -s CB K_p s - \\ &\quad sgn(s) s K(\mathbf{x}) [|CAe| + |C(A - A_m)\mathbf{x}_m| + \\ &\quad |CB_m\psi_r|] \times (\hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1))^2 + sgn(s) s [|CAe| + \\ &\quad |C(A - A_m)\mathbf{x}_m| + |CB_m\psi_r|] \hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1) - \\ &\quad sgn(s) s c_n [K(\mathbf{x}) \hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1) \hat{\Phi}_2(\mathbf{x}|\hat{\Theta}_2) - \\ &\quad \hat{\Phi}_2(\mathbf{x}|\hat{\Theta}_2)] + (s CAe + s C(A - A_m)\mathbf{x}_m - \\ &\quad s CB_m\psi_r) - sgn(s) s [|CAe| + |C(A - \\ &\quad A_m)\mathbf{x}_m| + |CB_m\psi_r|] \hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1^*) - [s c_n d(\mathbf{x}) + \\ &\quad sgn(s) s c_n \hat{\Phi}_2(\mathbf{x}|\hat{\Theta}_2^*)] \end{aligned} \quad (22)$$

The first term in (22) is:

$$\begin{aligned} &-s CB K_p s \\ &= -s c_n K(\mathbf{x}) K_p s \\ \text{While } c_n, K(\mathbf{x}) \text{ and } K_p &> 0 \text{ then} \\ &-s c_n K(\mathbf{x}) K_p s \leq 0 \end{aligned} \quad (23)$$

For further analysis, it is assumed that for the two continuous functions $\Phi_1(\mathbf{x})$ and $\Phi_2(\mathbf{x})$ defined in

(10) and (11) on a compact set, there exist two optimal weight vectors Θ_1^* and Θ_2^* such that:

$$|\varepsilon_1(\mathbf{x})| = |\hat{\Phi}_1(\mathbf{x}|\Theta_2^*) - \Phi_1(\mathbf{x})| < \delta_1 \quad (24)$$

$$|\varepsilon_2(\mathbf{x})| = |\hat{\Phi}_2(\mathbf{x}|\Theta_2^*) - \Phi_2(\mathbf{x})| < \delta_2 \quad (25)$$

And the uncertainty bounds $K_l(\mathbf{x})$ and $d_u(\mathbf{x})$ meet the following inequalities on the compact set:

$$0 < K_l(\mathbf{x}) < \frac{1}{1-\delta_1} \quad (26)$$

$$d_u(\mathbf{x}) - |d(\mathbf{x})| > \delta_2 \quad (27)$$

So, (22) can be written as below:

$$\begin{aligned} \dot{L}(s, \tilde{\Theta}) &= -s c_n K(\mathbf{x}) K_p s - \\ &\quad K_l(\mathbf{x}) |s| [(\hat{\Theta}_1^T(0) - \Theta_1^{*T}) \zeta_1(\mathbf{x}) + \\ &\quad \Gamma_1 (\int_0^t (|CAe| + |C(A - A_m)\mathbf{x}_m| + \\ &\quad |CB_m\psi_r|) |s| \zeta_1(\mathbf{x})) dt] \zeta_1(\mathbf{x}) - \delta_1 [|CAe| + \\ &\quad |C(A - A_m)\mathbf{x}_m| + |CB_m\psi_r|] \hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1) - \\ &\quad |s| (-K(\mathbf{x}) \hat{\Phi}_1(\mathbf{x}|\hat{\Theta}_1) + 1) |s| c_n \hat{\Phi}_2(\mathbf{x}|\hat{\Theta}_2) - \\ &\quad |s| (K_l^{-1}(\mathbf{x}) - (1 + \delta_1)) [|CAe| + |C(A - \\ &\quad A_m)\mathbf{x}_m| + |CB_m\psi_r|] - |s| c_n [\varepsilon_2(\mathbf{x}) + \delta_2] \end{aligned} \quad (28)$$

Its guarantee $\dot{L}(s, \tilde{\Theta}) < 0$. The state errors of the system are ensured to converge to zero. This complete the proof.

IV. SIMULATION Results

This section presents the results of a numerical simulation of the proposed combined neural network sliding mode and PD control performed to evaluate for ship steering controller and verify the stability of the system and the learning law.

The dynamics model of a warship traveling at 16 knots, considered has the following parameters [7, 10, 13]:

$$\begin{aligned} K &= 0.0107 \\ d_0 &= 0 \\ d_1 &= 9.42 \\ d_2 &= 0 \\ d_3 &= 2.24 \end{aligned}$$

The reference model is designed such that,

$$\begin{aligned} k_m &= 0.025 \\ a_m &= 0.45 \\ b_m &= 0.025 \end{aligned}$$

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