Paper:

Adaptive RBF Neural Network Sliding Model Control For Path Tracking Of DP Vessel

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Abstract. With external environmental disturbances and model uncertainties,a path tracking control method for Dynamic Positioning(DP) vessel is proposed.It addressed the problem of the accuracy of path tracking and improved the convergence rate of errors.First,a 3-degree of freedom horizontal motion model is established.Then,considering input saturation,an adaptive radial basis function neural network(RBFNN) sliding mode controller is designed to realize the tracking of desired path, and detailed stability proof illustrates that all errors are bounded.At last, a series of simulations verify the accuracy and validity of the proposed control strategy.

Keywords: path tracking, RBF, sliding mode control, dynamic positioning, model uncertainties

1. Introduction

In recent years, with the frequent exploitation of oil and gas resources, land resources have been decreasing year by year[1]. there has been an increasing interest in ocean resources.developments in offshore resources exploitation platform have heightened the need for abundant energy in marine.Due to the characteristic of not being limited by water depth,the dynamic positioning vessel has always been an important platform for the development of marine resources.The problem of path tracking is the basic research direction of ship dynamic positioning control.How to improve the accuracy of path tracking and the convergence rate of errors are the frequently stated problems in DP control field.

Many scholars have devoted to the research of path tracking control for vessel, and applied various control methods such as sliding model control(SMC)[2], PID control[3], adaptive control[4], backstepping control[5] and so on to improve the performance of ship motion.A nonlinear controller based on an backstepping algorithm to solve the robust control problem of a dynamic positioning vessel was proposed in [6], but this method ignored the problem of input saturation and differential explosion of controller design.A constrained model predictive control (MPC) algorithm based dynamic positioning system was applied in [7],which simplified the design of control law.However,the linearized ship model decreased the control accuracy, so that the DP system was not suitable for harsh marine environments.Considering unknown time-varying environment disturbances and transient performance,a terminal sliding mode surface was designed to guarantee the stability of the system in harsh environments in [8].The above control laws were based on the accurate system model.However,a exact ship model is hard to obtain under complex environments.A robust adaptive neural network control law was designed in [9],It not only simplified the computational burden of the controller, but also compensated for the uncertainties of the system model by introducing the neural network.

Inspired by the aforementioned researches,an adaptive radial basis RBF neural network sliding model controller is designed for the path following problem of dynamic positioning vessel.The controller not only suppresses the external time-varying disturbances, but also compensates the uncertainties of the system model.

The rest of this paper is organized as follows. The model of dynamic positioning vessel is introduced in Section 2. The design of control scheme is advanced in Section 3, including controller design and stability analysis.Simulations and comparisons to illustrate the accuracy of tracking control algorithm is given in section 4. The conclusions are finally concluded in Section 5.

2. Modelling and Preliminaries

2.1. Dynamic Positioning Vessel Model

$O-x_ny_nz_n$ and $O-x_by_bz_b$ are the North-East-down(NED) and body-fixed frames respectively in Fig.1. x,y,z and φ,θ,ψ are the position and the Euler angle in NED coordinate system; u,v,w and p,q,r are the linear velocities and the angular velocities in

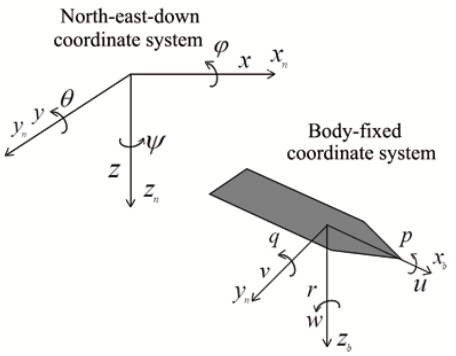


Fig. 1. The coordinate for DP motion description

body-fixed coordinate system.A 3-degree of freedom horizontal motion model is established. The kinematics model of DP vessel represents the transformation relationship of variables between the NED coordinate system and the body-fixed coordinate system, while the dynamics model describes the low-speed movement of DP vessel in the horizontal plane, which is respectively given by

$$\begin{cases} \dot{\eta} = R(\psi)\upsilon \\ M\dot{\upsilon} = \tau - D\upsilon + d(t) \end{cases} \tag{1}$$

Where $\eta = \begin{bmatrix} x & y & \psi \end{bmatrix}^T$, $\upsilon = \begin{bmatrix} u & v & r \end{bmatrix}^T$, M is the generalized rigid body inertia matrix and D is the nonlinear damping coefficient matrix; $\tau = \begin{bmatrix} \tau_1 & \tau_2 & \tau_3 \end{bmatrix}^T$ is the control input vector produced by the propulsion system. $d(t)$ is the disturbances from wind, waves and currents; $R(\psi)$ is the rotation matrix and given by

$$R(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

2.2. Adaptive RBF Neutral Network Model

Due to the unknown parameters in the dynamic positioning system,an accurate ship model is difficult to establish.Furthermore,uncertainties of the model increase the difficulty of the stability analysis of the dynamic positioning system,and even lead to the failure of the tracking task.Neural networks have the great advantages in approximating arbitrary nonlinear systems.Therefore, an adaptive RBF neural network model is established,which can approximate the continuous system model greatly[10].

A RBF neural network is chosen to estimate the uncertain terms of the ship model, and the process of estimation algorithm are as following

$$f(\theta) = W^{*T}P(\theta) + \kappa(\theta) \tag{3}$$

Where $\theta = [\theta_1, \theta_2, \cdots, \theta_m]^T \in \Omega_\theta$ is input state vector and Ω_θ is a compact set.$P(\theta) = [p_1(\theta), p_2(\theta), \cdots, p_n(\theta)]^T$ is activation function in Neural Network Model,$\kappa(\theta)$ is the estimate error, $W^* = [w_1^*, w_2^*, \cdots, w_n^*]^T$ is the ideal weight vector and given by

$$W^* = \arg\min\left[\sup\left|f(\theta) - W^T P(\theta)\right|\right] \tag{4}$$

Where $W = [w_1, w_2, \cdots, w_n]^T$.

The Gaussian function is selected as activation function of the RBF neural network,which is expressed as

$$p_i(\theta) = \exp\left[-\frac{\|\theta - \chi_i\|^2}{2\iota_i^2}\right], i = 1, 2, \cdots, n \tag{5}$$

where $\iota_i > 0$ and $\chi_i = [\chi_{i1}, \chi_{i2}, \cdots, \chi_{in}]^T$ represents the width of the ith neuron and the ith center vector respectively.

***Assumption*1.** $\kappa(\theta)$ and W^* are bounded,$\exists \kappa_m > 0$ and $W_m > 0$ such that $|\kappa(\theta)| \le \kappa_m$ and $|W^*| \le W_m$.

3. Adaptive RBF Sliding Mode Controller Design

In this section, fully considering the uncertainties of the system model and external disturbances,an adaptive neural network sliding mode control controller is constructed by combining the RBF neural network with the sliding mode control, and the stability of the designed controller is proved.

The dynamic positioning vessel is influenced by the actuator input constraints in engineering practice, which will seriously affect the stability of the control system. Therefore, considering the limitation of thrusters, the saturation function is defined as[11]

$$sat(\tau) = [sat(\tau_1), sat(\tau_2), sat(\tau_3)]^T \tag{6}$$

Eq.(6) can be written as

$$sat(\tau) = \Theta(\tau_u)\tau_u \tag{7}$$

Where $\Theta(\tau_u) = diag(\Theta\tau_{u1}), \Theta(\tau_{u2}), \Theta(\tau_{u3}))$,and $\Theta(\tau_u)$ can be experssed as

$$\Theta(\tau_{ui}) = \begin{cases} 1, |\tau_{ui}| \le \tau_{ui\max} \\ \mathrm{sgn}(\tau_{ui})\tau_{ui\max}, otherwise \end{cases} \tag{8}$$

Where $i = 1, 2, 3, \tau_{i\max}$ is the maximum value of the ith control input.

The dynamic positioning system model is transformed into

$$\begin{cases} \dot{\eta} = R(\psi)\upsilon \\ M\dot{\upsilon} = -D\upsilon + \Theta(\tau_u)\tau_u + d(t) \end{cases} \tag{9}$$

Then, the motion equation with model uncertainties is modeled as

$$\begin{cases} \dot{\eta} = R(\psi)\upsilon \\ (M_0 + \Delta M)\dot{\upsilon} = -(D_0 + \Delta D)\upsilon + \Theta(\tau_u)\tau_u + d(t) \end{cases} \tag{10}$$

Taking the derivative of both side of the first equation of Eq.(10),we have

$$\dot{\upsilon} = R^T(\psi)\ddot{\eta} - R^T\dot{R}\upsilon \tag{11}$$

According to Eq.(10) and Eq.(11) the following equality is obtained.

$$\begin{aligned}\ddot{\eta} &= RM_0^{-1}\Theta(\tau_u)\tau_u - RM_0^{-1}(D_0 - M_0R^T\dot{R})\upsilon + RM_0^{-1}d \\ &-RM_0^{-1}\Delta MR^T\ddot{\eta} + RM_0^{-1}(\Delta MR^T\dot{R} - \Delta D)\upsilon\end{aligned} \tag{12}$$

Finally,we can get the expression of $\ddot{\eta}$ as

$$\ddot{\eta} = RM_0^{-1}\Theta(\tau_u)\tau_u - RM_0^{-1}(D_0 - M_0R^T\dot{R})\upsilon + RM_0^{-1}\Delta \tag{13}$$

Where $\Delta = d - \Delta MR^T\ddot{\eta} + (\Delta MR^T\dot{R} - \Delta D)\upsilon$ which represents unknown environmental disturbances and system uncertainties.

Choose sliding surface as[12]

$$s = \dot{e} + k_1 e \tag{14}$$

Where $e = \eta - \eta_d$,η_d is the desired position vector.

Let $x_1 = \eta$ and $x_2 = \dot{x}_1$,we have

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = RM_0^{-1}\Theta(\tau_u)\tau_u - RM_0^{-1}(D_0 - \\ M_0R^T\dot{R})\upsilon + RM_0^{-1}\Delta \end{cases} \tag{15}$$

Taking the derivative of Eq.(14)

$$\begin{aligned}\dot{s} &= \ddot{e} + k_1\dot{e} \\ &= \ddot{\eta} - \ddot{\eta}_d + k_1(\dot{\eta} - \dot{\eta}_d) \\ &= RM_0^{-1}\left(\Theta(\tau_u)\tau_u - (D_0 - M_0R^T\dot{R})\upsilon\right) \\ &+k_1R\upsilon + RM_0^{-1}\Delta - \ddot{\eta}_d - k_1\dot{\eta}_d\end{aligned} \tag{16}$$

The approach law can be chosen as[13]

$$\begin{aligned}\dot{s} &= RM_0^{-1}\left(\Theta(\tau_u)\tau_u - (D_0 - M_0R^T\dot{R})\upsilon\right) \\ &+k_1R\upsilon + RM_0^{-1}\Delta - \ddot{\eta}_d - k_1\dot{\eta}_d \\ &= -k_2s - \varepsilon\mathrm{sgn}(s)\end{aligned} \tag{17}$$

Then we can get

$$\begin{aligned}RM_0^{-1}\Theta(\tau_u)\tau_u &= RM_0^{-1}(D_0 - M_0R^T\dot{R})\upsilon - k_1R\upsilon \\ &-RM_0^{-1}\Delta + \ddot{\eta}_d + k_1\dot{\eta}_d - k_2s - \varepsilon\mathrm{sgn}(s)\end{aligned} \tag{18}$$

Control input is obtained by considering of the input saturation as

$$\begin{aligned}\Theta(\tau_u)\tau_u &= M_0R^{-1}(-k_2s + \ddot{\eta}_d - \dot{R}\upsilon - \\ &k_1R\upsilon - k_1\dot{\eta}_d) + D_0\upsilon - \Delta\end{aligned} \tag{19}$$

Using a neural network to estimate Δ

$$\begin{aligned}\Delta &= d - \Delta MR^T\ddot{\eta} + (\Delta MR^T\dot{R} - \Delta D)\upsilon \\ &= W^{*T}P(\theta) + \kappa(\theta)\end{aligned} \tag{20}$$

Finally ,the control law τ_u can be obtained as

$$\begin{aligned}\tau_u &= \Theta^{-1}M_0^{-1}R^{-1}(-k_2s + \ddot{\eta}_d - \dot{R}v - k_1Rv - k_1\dot{\eta}_d) \\ &+\Theta^{-1}D_0v - \Theta^{-1}\hat{W}^TP\end{aligned} \tag{21}$$

At the same time, the adaptive update law of the control system is

$$\dot{\hat{W}} = \Gamma^{-1}Ps^TRM_0^{-1} \tag{22}$$

Where Γ is the constant coefficient matrix to be designed.

***Theorem*1** For DP system with input saturation, model uncertainties and external time-varying disturbances,the RBF neural network sliding mode controller Eq.(21) and the adaptive update law Eq.(22) render the closed-loop system can reach $\dot{s} = 0$. All errors signals of closed-loop DP system are bounded.

***proof*:** Define Lyapunov function V_1 as

$$V_1 = 1/2s^Ts \tag{23}$$

Taking derivate of V_1

$$\begin{aligned}\dot{V}_1 &= s^T\dot{s} \\ &= s^TRM_0^{-1}\left(\Theta(\tau_u)\tau_u - (D_0 - M_0R^T\dot{R})v\right) \\ &+s^Tk_1Rv + s^TRM_0^{-1}\Delta - s^T\ddot{\eta}_d - s^Tk_1\dot{\eta}_d\end{aligned} \tag{24}$$

Substituting Eq.(21) into Eq.(24) yields

$$\begin{aligned}\dot{V}_1 &= -s^Tk_2s - s^T\varepsilon\mathrm{sgn}(s) - s^TRM_0^{-1}\hat{W}^TP \\ &+s^TRM_0^{-1}W^{*T}P + s^TRM_0^{-1}\kappa \\ &= s^T(-k_2s - \varepsilon\mathrm{sgn}(s) + RM_0^{-1}\tilde{W}^TP + RM_0^{-1}\kappa) \\ &\le s^T(-k_2s - \varepsilon\mathrm{sgn}(s) + RM_0^{-1}\tilde{W}^TP) + s^T\left\|RM_0^{-1}\kappa\right\|\end{aligned} \tag{25}$$

Define global Lyapunov function as

$$V = \frac{1}{2}s^Ts + \frac{1}{2}\tilde{W}^T\Gamma\tilde{W} \tag{26}$$

Taking derivative of V

$$\begin{aligned}\dot{V} &= s^T\dot{s} + \tilde{W}^T\Gamma\dot{\tilde{W}} \\ &\le s^T(-k_2s - \varepsilon\mathrm{sgn}(s) + RM_0^{-1}\tilde{W}^TP) + s^T\left\|RM_0^{-1}\kappa\right\| + a \\ &\le s^T(-k_2s - \varepsilon\mathrm{sgn}(s) + RM_0^{-1}\tilde{W}^TP) + s^T\left\|RM_0^{-1}\kappa\right\| + b \\ &\le s^T\left(-k_2s - \varepsilon\mathrm{sgn}(s) + \left\|RM_0^{-1}\kappa\right\|\right) - \tilde{W}^TPs^TRM_0^{-1} + b \\ &\le -\varepsilon\|s\| - k_2s^2 \le 0\end{aligned} \tag{27}$$

Where $a = \tilde{W}^T\Gamma\dot{\tilde{W}}$,$b = -\tilde{W}^T\Gamma\dot{\hat{W}}$.

Thus,according to Eq.(14),the sliding mode s and tracking errors e are bounded.since the desired path η_d and $\dot{\eta}_d$ are bounded,the real path η and velocities υ are also bounded.

4. Simulation And Results

In order to verify the effectiveness of the controller for path tracking of DP vessel,several comparisons

Table 1. Perfprmance parameters.

Name	Value
Ship length	204.65(m)
Ship width	39.20(m)
Draft	11(m)
operating draft	7.00-9.54(m)
displacement	59106.60(t)
Water depth	15.00-3000(m)

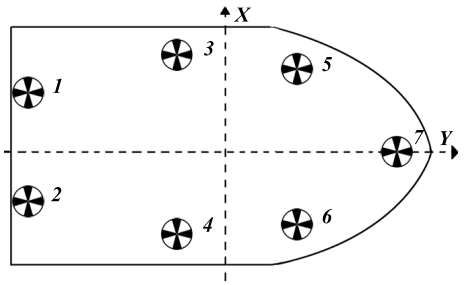


Fig. 2. The thruster position distributions of DP vessel

are set up.

Specific parameters are set as follows. The simulation time is 1500.Initial ship position and speed vector are $\eta(0) = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$ and $\upsilon(0) = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$ respectively.The data of DP vessel model are shown in Table 1[14] and the parameter matrix information of the dynamics model Eq.(1) are

$$M = \begin{bmatrix} 2.769\times10^7 & 0 & 0 \\ 0 & 5.160\times10^7 & 4.836\times10^8 \\ 0 & 4.836\times10^8 & 4.509\times10^{10} \end{bmatrix} \tag{28}$$

$$D = \begin{bmatrix} 1.096\times10^5 & 0 & 0 \\ 0 & 1.373\times10^5 & -3.118\times10^6 \\ 0 & 2.903\times10^6 & 7.264\times10^8 \end{bmatrix} \tag{29}$$

Considering redundancy and robustness of DP system, DP vessels are usually equipped with more than three thrusters.The ship in this paper have seven thrusters.The distribution of thrusters can be seen from Fig.2.

The thruster position distributions of DP vessel are $(-93.8m, 9.45m)$, $(-93.8m, -9.45m)$, $(-12.55m, 15.4m)$, $(-12.55m, \ -15.4m)$, $(37.85m, 14m)$, $(37.85m, -14m)$ and $(82.65m, 0m)$ respectively.

The maximum thrust output values are $680KN, 680KN, 540KN, 540KN, 540KN, 540KN, 540KN$ respectively.The control output can be expressed as

$$sat(\tau) = Tu \tag{30}$$

Where u is the thruster output vector,$T \in \Re^{3\times7}$ is the thruster distribution matrix,which can be designed as

$$T = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 \\ 9.5 & -9.5 & -12.5 & -12.5 & 37.8 & 37.8 & 0 \end{bmatrix} \tag{31}$$

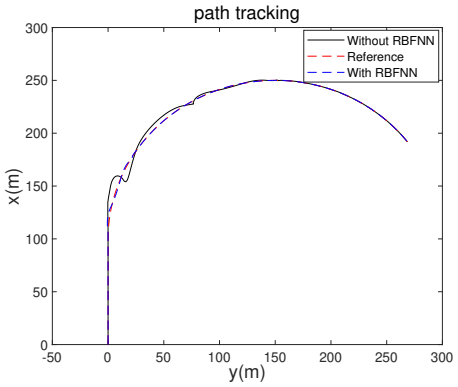


Fig. 3. Comparison of path tracking

According to the requirement of trajectory tracking task for dynamic positioning vessel, a trajectory is designed which is composed of straight lines and curves as

$$\eta_d = \begin{cases} [t,0,0]^T, if\ t \le 50 \\ [100\sin(0.01(t-50))+50, 100(1- \\ \cos(0.01(t-50))), 0.01(t-50)^T, if\ t > 50 \end{cases} \tag{32}$$

The time-varying interference is considered as follows.

$$d(t) = R^T(\eta) d_f(t) \tag{33}$$

Where $d_f(t) = [2000 + 0.7\sin(0.6t) + 0.3\sin(0.4t) + 0.3\sin(0.8t), 2000, 2000]^T$.

The controller parameters are set as follows.$t = 300s, k1 = diag(3,3,3), k2 = diag(15,15,15), \Gamma = 1\times10^6 I_{729\times729}$,the initial value of the weight vector is $\hat{W}_i(0) = 0_{729\times1} (i = 1,2,3)$ the simulation step length is $0.005s$.

A comparison is conducted to show the control effects of the designed controller,which is shown in Fig.3,Fig.4 and Fig.5.

Fig.3 and Fig.4 are shown the simulation results of time response of the path tracking and the position and posture.From Fig.3,both controller with RBFNN and without RBFNN can get desired tracking effects in straight line tracking.However, in the process of curve tracking, the the adaptive RBFNN sliding mode controller show better performance in robustness and accuracy than the sliding mode controller, which reflects that RBF can overcome the decrease of control accuracy caused by model uncertainties. Fig.5 show the tracking errors of position and posture.The tracking errors of DP vessel by using controller with RBFNN are less than

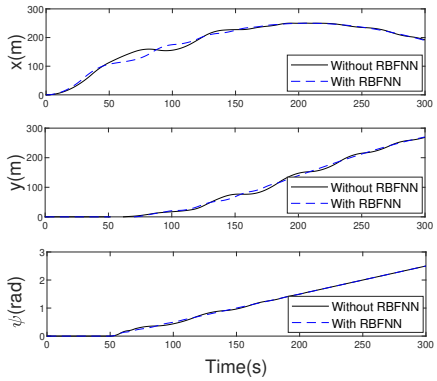


Fig. 4. Comparison of position and posture

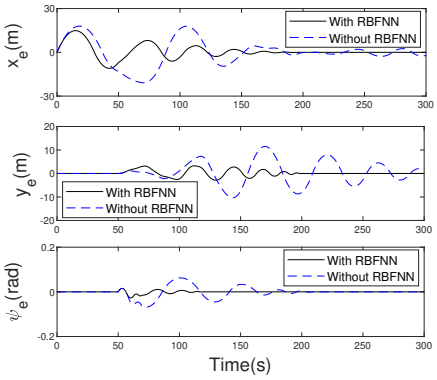


Fig. 5. Comparison of the tracking error

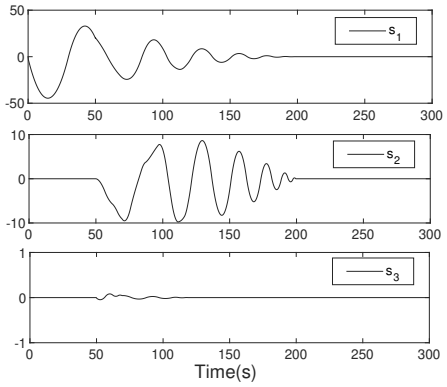


Fig. 6. Time response of proportional-derivative sliding mode surface

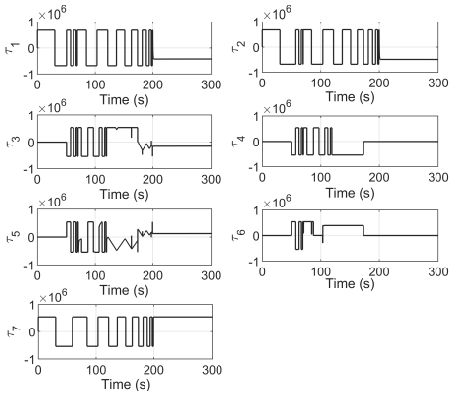


Fig. 7. Time response of control force outputs of the thrusters

without RBFNN,and error convergence speeds of DP control system with RBFNN are faster than without RBFNN.

Fig.6 is the time response of the proportional-derivative sliding mode surface designed in the controller.The state trajectory of the control system can moves to the sliding surface without chattering from the picture,and the tracking errors will converge to small neighborhoods.

Fig.7shows the actual control output response of the propulsion system of the dynamic positioning vessel.The thrust forces not exceed the setting maximum value, which solves the saturation problem from another perspective.Although fluctuations exist with the changes of thrust force, there is little effect on the whole control system.

5. Conclusion

An adaptive RBF neural network sliding mode control method is proposed to realize the path tracking of dynamic positioning vessel.RBF neural network is introduced to deal with the model uncertainties,which improves the robustness of controller.In the view of the great performance of sliding mode control on response speed, a combined controller is designed to acheive the tracking goal under internal and external uncertainties.The boundedness of closed-loop system errors are proved by using Lyapunov function,and the simulation results have shown the effectiveness of designed controller.

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