Journal of Marine Science and Technology manuscript No.
(will be inserted by the editor)

Online Learning Control of Surface Vessels for Fine Trajectory Tracking

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Received: date / Accepted: date

Abstract This paper presents an adaptive neural network (NN) controller for fine trajectory tracking of surface vessels with uncertain environmental disturbances. Regarding to the new demands for fine trajectory tracking, especially to the requirement of high accuracy tracking in limited working space, the proposed NN controller is designed to contain a tracking error control component and a velocity error control component, aiming to converge both types of error to zero, separately. It utilizes radial basis functions to approximate a vessel's unknown nonlinear dynamics. Therefore, there is no need of any explicit knowledge of the vessel. The online learning ability is obtained during the stability analysis by using the backstepping technique and the Lyapunov theory. Theoretical results guarantee both the convergence of tracking error and velocity error and the boundedness of NN update. Through simulation and tracking performance study based on the CyberShip II model, the proposed controller is verified effective in fine trajectory tracking.

Keywords Adaptive neural controller · Trajectory tracking · Online learning · Surface vessels

1 Introduction

The dynamic positioning (DP) formulation was motivated by marine applications in which a vessel can accurately maintain both its position and heading at a fixed location or pre-determined paths by means of thruster forces [1]. DP technique has made many marine operations come true, such as deep sea exploration, offshore oil

This work is supported by a grant from the "Marine Operations in Virtual Environments" project in Norway.

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Fig. 1 Fine trajectory tracking.

drilling and pipeline maintenance. From the guidelines for vessels with DP systems issued by the International Maritime Organization, vessels with DP systems are conducive to increase maneuverability under specified maximum environmental conditions. DP systems have been employed for ships, mobile offshore drilling units, offshore support vessels and oceanographic research vessels. Nowadays, due to the theoretical challenges of DP technique and the growth of emerging demands from offshore applications, developing new types of DP systems is challenging.

In the literature, there are two challenges for designing efficient DP systems [2]. First, because the dynamics of the vessel varies with navigational status such as the load and the speed during DP operations, its dynamics is nonlinear and time-varying. It is impossible to fully depict the dynamical behavior using current modeling techniques. Therefore, in the early research, controllers for DP systems were designed with an assumption of linearizing the dynamics model. A lot of model-based adaptive controllers were developed by researchers based on the assumption [3–5]. Recently, Some robust controllers based on the techniques, such as Lyapunov's direct method [6], backstepping technique [7] and sliding mode control [8], have shown low sensitivity to parameter variations and disturbances. Although they can accomplish the model-based controller design, they still rely on the knowledge of the dynamics model. The second challenge is derived from the operation environment. Environmental perturbation such as waves, wind and currents is complex and unpredictable. However, its effect on DP systems cannot be neglected. More recently, some passive nonlinear observers were presented [9] [10]. By estimating the constant or the time-varying disturbances, compensating control laws were designed to improve the DP accuracy. Although the two DP challenges are solved by aforementioned results to some extent, they still attract a lot of attention from marine technology communities.

To date, with the development of approximation-based control techniques, breakthrough achievements have been made for DP systems. A good number of novel intelligent control methods such as fuzzy control and neural network (NN) control were proposed [11–18]. Owing to the approximation capability of learning and adaptation, there is no need to spend much effort on system modeling. Chang et al. designed a Takagi-Sugeno type fuzzy model to represent the nonlinear system by using a set of fuzzy rules[11]. In [12], a novel model reference adaptive robust fuzzy control algorithm was proposed to approximate unknown functions including lumped model parameters and external disturbances for ship course-keeping tasks. Skjetne et al. used an adaptive recursive design method to describe a parametrically uncertain ship and applied it on dynamic maneuvering[16]. Leonessa et al. proposed a NN model reference controller to improve the control performance in terms of tracking in the presence of unmodeled dynamics [13]. Tee and Ge developed a single-layer NN as a linearly parameterized approximator of ship uncertainties and unknown disturbances for trajectory tracking [14]. Pan et al. presented similar work by using a regressor to express the highly nonlinear dynamics of a vessel [15]. Both Dai et al. and Xia et al. employed a radial basis function in NN to estimate and compensate the uncertainties of ship dynamics and environmental disturbances [17] [18]. According to the backstepping technique and the Lypunov theory, they succeeded to improve the control performance and reduce the tracking errors.

From a control point of view, fuzzy control is nontrivial and time consuming in practise since it obtains rules mainly by trial and error from experiences. In contrast, adaptive NN control is capable of deterministic learning, i.e., online adjusting unknown control model parameters. Therefore, adaptive NN control is superior to fuzzy control, especially when controlling complex, nonlinear and uncertain systems. Unlike classical statistical learning theory, an online learning NN is designed based on deterministic learning theory [19]. With deterministic learning, fundamental knowledge for system dynamics can be identified by the online learning NN through accumulating and storing historical data, and meanwhile represented in a deterministic manner. Unfortunately, the key ability of online learning of NN control is seldom addressed in DP system design in the literature.

Our project aims to make the best use of the NN learning ability and develop NN-based controllers for DP systems to achieve real-time control of marine vessels. In this paper, we emphasize the design of an adaptive NN controller for fine trajectory tracking tasks. Fine trajectory tracking is a new demand in offshore operations, which requires fine maneuvering of marine vessels around target object, as shown in Fig. 1. Fine manoeuvring not only requests low speed of vessels and high position control accuracy, but also has very strict and limited working spaces during offshore operations. To release the burden of the operators and increase the safety of operations, we propose an adaptive NN controller for fine manoeuvring. The main contributions of this paper include:

– An adaptive NN control algorithm together with a stability proof is proposed with unknown ship dynamics.
– A complete simulation for online learning of ship dynamics is carried out using the Cybership II ship model [20].

The paper is organized as follows. Section 2 introduces the NN model and the description of dynamics of a vessel. In Section 3, the adaptive NN controller is presented in detail. The simulation and some performance studies are shown in Section 4, which is followed by discussions in Section 5. Conclusions and future work are given finally.

2 Related Work

2.1 Radial basis function neural network

Radial basis function neural network (RBFNN) is a type of feedforward approximator and is usually used to approximate continuous nonlinear functions [21].

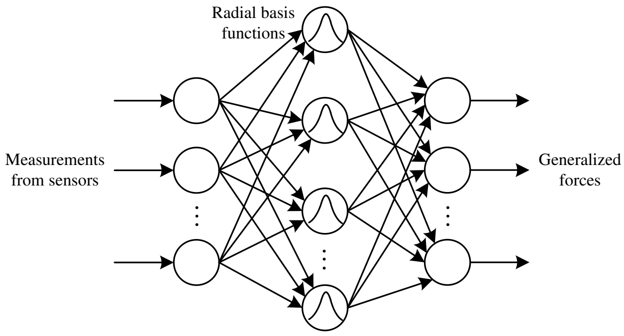

Fig. 2 Structure of the RBFNN.

It contains three layers: input layer, hidden layer and output layer, as shown in Fig. 2. In this paper, we take measurements from sensors as inputs and use the RBFNN to generate forces for fine manoeuvring.

Assume the number of nodes in the three layers of the RBFNN are m, n, and p, respectively. Let $X = [x_1, x_2, ..., x_m]^T$ be the input vector and $H = [h_1, h_2, ..., h_n]^T$ be the hidden vector. The mapping from the input layer to the hidden layer is nonlinear. Here we use Gaussian function, the most commonly used radial basis function to approximate a nonlinear function:

$$h_i = exp(-\|X - \mu_i\|^2/2\sigma_i^2), \quad i = 1, 2, ..., n \tag{1}$$

where $\mu_i = [\mu_{i1}, \mu_{i2}..., \mu_{im}]^T$ is the center of the i-th Gaussian function and σ_i is the width of the i-th Gaussian function. The mapping from the hidden layer to the output layer is linear. We define $W \in R^{n\times p}$ as the weigh matrix between the two layers. Then the nonlinear function is described as:

$$F(X) = W^T H + \epsilon(X) \tag{2}$$

where ϵ is the approximation error. In [21], it has been shown that if the node number n in the hidden layer is large enough, the RBFNN output $W^T H$ can smoothly approximate the nonlinear function by online updating W towards the ideal weight matrix W^*:

$$W^* = \underset{W^* \in R^{n\times p}}{\operatorname{argmin}} \{\sup |\epsilon(X)|\} \tag{3}$$

2.2 Ship dynamics

For a horizontal motion of a fully actuated surface vessel, only three motion components including surge, sway and yaw are taken into consideration. The other motion components are neglected. According to Fossen [2], the DP system model in the presence of disturbances can be described as:

$$\dot{\eta} = J(\eta)\nu \tag{4}$$

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + \Delta = \tau \tag{5}$$

where

$$J(\eta) = \begin{bmatrix} \cos(\psi) & \text{-}\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

is the rotation matrix. The vector $\eta = [x, y, \psi]^T$ contains the positions (x, y) and the heading ψ of the vessel in the earth-fixed frame. The vector $\nu = [u, v, r]^T$ represents velocities in surge, sway and yaw in the body-fixed frame, respectively. $M \in R^{3\times3}$ is the system inertia matrix. $C(\nu) \in R^{3\times3}$ is the Coriolis and centripetal terms. $D(\nu) \in R^{3\times3}$ is the damping matrix. $\Delta \in R^3$ is the environmental disturbance vector. $\tau \in R^3$ is the vector of the generalized control forces consisting of the surge force, the sway force and the yaw moment.

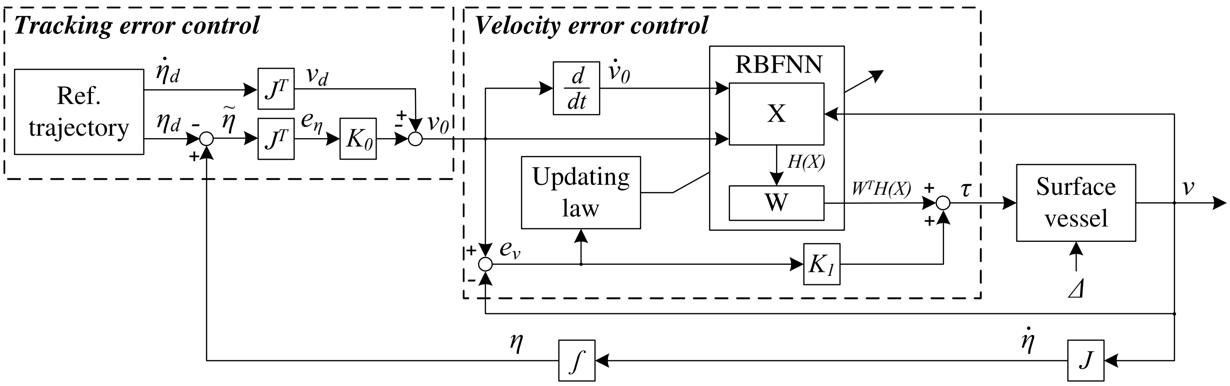

Fig. 3 Block diagram of the control system.

Although the matrix M that contains the mass, inertia and the added masses can be obtained accurately by using potential analysis, and several terms in C and D matrices can be obtained with good accuracy using conventional methods and softwares, it is difficult to design the control law without a fully obtained hydrodynamic parameters in these matrices. In addition, the environmental disturbances Δ cannot be identified and compensated easily. Thus, the control problem lies in how to develop a NN-based method to approximate the unknown dynamics from both the vessel and the environment and how to achieve efficient online learning law for fine trajectory tracking.

3 Adaptive NN Controller Design

In this section, we design an adaptive NN controller for fine trajectory tracking by combining the backstepping technique with a RBFNN.

Fig. 3 shows the whole structure of the control system. It contains two components: the tracking error control and the velocity error control. The tracking error control is designed to generate a speed control command based on the reference trajectory. While the velocity error control is designed to further generate the control law of the surface vessel. It takes the speed control command as input and uses the RBFNN to approximate the unknown nonlinear dynamics. Through Lyapunov stability analysis, the online updating law is derived. The system stability and convergence are both guaranteed. The following describes the controller in detail.

The dynamic model in (5) has the following properties [2]:

1). The matrix M is symmetric positive definite;
2). The matrix D is positive definite;
3). The matrix $\dot{M} - 2C$ is skew-symmetric.

We assume that:

1). Both η and ν are available without measurement error;
2). The disturbance Δ is slowly time-variant and bounded;
3). The desired trajectory $\eta_d(t)$ is smooth enough.

Assumption 3) indicates the time derivative $\dot{\eta}_d$ and $\ddot{\eta}_d$ can be obtained from a trajectory planner. The desired speed ν_d in the body-fixed frame is defined as:

$$\nu_d = [u_d, v_d, r_d]^T = J^{-1}(\eta)\dot{\eta}_d. \tag{7}$$

Let $\tilde{\eta} = \eta - \eta_d$ be the tracking error in the earth-fixed frame and e_η be the corresponding tracking error in the body-fixed frame. According to (4), e_η satisfies:

$$e_\eta = J^{-1}(\eta)\tilde{\eta}. \tag{8}$$

Noting the property $JJ^T = I$ and taking the time derivative of (8) yield

$$\dot{e}_\eta = \dot{J}^T(\eta)\tilde{\eta} + J^T(\eta)\dot{\tilde{\eta}}. \tag{9}$$

In addition, we have the derivative of $J(\eta)$ from (6):

$$\dot{J}(\eta) = J(\eta)S(r) \tag{10}$$

where

$$S(r) = \begin{bmatrix} 0 & \text{-r} & 0 \\ \text{r} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \tag{11}$$

By substituting (4), (7), (8), (10) and (11) into (9), we obtain the derivative of tracking error in the body-fixed frame:

$$\dot{e}_\eta = S^T(r)e_\eta + \nu - \nu_d. \tag{12}$$

Consider a Lyapunov function candidate:

$$V_1 = \frac{1}{2}e_\eta^T e_\eta. \tag{13}$$

Its derivative is:

$$\begin{aligned} \dot{V}_1 &= e_\eta^T \dot{e}_\eta \\ &= e_\eta^T S(r)e_\eta + e_\eta^T(\nu - \nu_d). \end{aligned} \tag{14}$$

Here we choose the velocity ν to follow a command velocity ν_0, i.e.,

$$\nu \equiv \nu_0 = \nu_d - K_0 e_\eta \tag{15}$$

where $K_0 \in R^{3\times 3}$ is a diagonal positive definite design parameter matrix. Noting that $S(r)$ in (11) is skew-symmetric and thus substituting (15) into (14) yields

$$\dot{V}_1 = -e_\eta^T K_0 e_\eta \leq 0. \tag{16}$$

Note $\dot{V}_1 = 0$ only if $e_\eta = 0$, which means the tracking error e_η under the speed control command (15) is asymptotically stable.

In order to ensure the velocity ν to follow the command velocity ν_0, the control force τ in (5) should be properly designed. Define the velocity error as

$$e_\nu = \nu_0 - \nu. \tag{17}$$

Using (5) and taking the derivative of e_ν, we obtain

$$\dot{e}_\nu = M^{-1}[-\tau - Ce_\nu + M\dot{\nu}_0 + C\nu_0 + D\nu + \Delta]. \tag{18}$$

Consider the Lyapunov function candidate V_2:

$$V_2 = V_1 + \frac{1}{2} e_\nu^T M e_\nu. \tag{19}$$

According to (18) and the property 3) of (5), the time derivative of V_2 becomes

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + e_\nu^T M \dot{e}_\nu + \frac{1}{2} e_\nu^T \dot{M} e_\nu \\ &= \dot{V}_1 + e_\nu^T [-\tau + M\dot{\nu}_0 + C\nu_0 + D\nu + \Delta]. \end{aligned} \tag{20}$$

Here we use a RBFNN f to approximate the uncertainty of the ship dynamics:

$$f = W^T H(X) = M\dot{\nu}_0 + C\nu_0 + D\nu + \Delta \tag{21}$$

where $W \in R^{n\times 3}$ is the weight matrix of the RBFNN; n is the number nodes in the hidden layer of the RBFNN; $X = [\dot{\nu}_0, \nu_0, \nu]^T$ is the input vector of the RBFNN; and H is the hidden vector with Gaussian basis function. We further design the control law as:

$$\tau = \hat{W}^T H(X) + K_1 e_\nu \tag{22}$$

where $\hat{W} \in R^{n\times 3}$ is the estimated weight matrix of the RBFNN and $K_1 \in R^{3\times 3}$ is a positive definite matrix. Substituting (21) and (22) into (20) obtains

$$\dot{V}_2 = \dot{V}_1 - e_\nu^T K_1 e_\nu - e_\nu^T \tilde{W}^T H(X) \tag{23}$$

where $\tilde{W}^T = \hat{W}^T - W^T$ represents the estimate error of the weight matrix of the RBFNN. Since the last term of (23) cannot guarantee non-positive of $\dot{V}_2$, we have to further design the updating law for the weight matrix of the RBFNN. Again, we choose the Lyapunov function candidate V_3 as

$$V_3 = V_2 + \frac{1}{2} tr(\tilde{W}^T \Theta \tilde{W}) \tag{24}$$

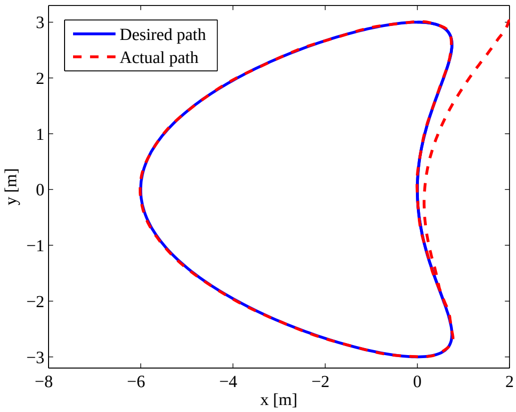

Fig. 4 Tracking result in xy-plane under time-variant disturbances.

where $\Theta \in R^{n\times n}$ is a diagonal positive definite design square matrix; tr represents the trace, i.e., the sum of the elements on the main diagonal of a square matrix. By differentiating V_3 with respect to time, we get:

$$\begin{aligned}\dot{V}_3 &= \dot{V}_2 + tr(\tilde{W}^T\Theta\dot{\tilde{W}}) \\ &= \dot{V}_1 - e_\nu^T K_1 e_\nu - e_\nu^T\tilde{W}^T H(X) + tr(\tilde{W}^T\Theta\dot{\tilde{W}}).\end{aligned} \tag{25}$$

Note that the term $e_\nu^T\tilde{W}^T H(X)$ is a scalar. According to the switch property of trace of a product $tr(AB) = tr(BA)$, (25) can be rewritten as:

$$\begin{aligned}\dot{V}_3 &= \dot{V}_1 - e_\nu^T K_1 e_\nu - tr(e_\nu^T\tilde{W}^T H(X)) + tr(\tilde{W}^T\Theta\dot{\tilde{W}}) \\ &= \dot{V}_1 - e_\nu^T K_1 e_\nu - tr(\tilde{W}^T H(X)e_\nu^T) + tr(\tilde{W}^T\Theta\dot{\tilde{W}}) \\ &= \dot{V}_1 - e_\nu^T K_1 e_\nu + tr(\tilde{W}^T(-H(X)e_\nu^T + \Theta\dot{\tilde{W}})).\end{aligned} \tag{26}$$

If we choose the updating law as

$$\dot{\hat{W}} = \dot{\tilde{W}} = \Theta^{-1}H(X)e_\nu^T, \tag{27}$$

$\dot{V}_3$ can be shown to be non-positive:

$$\dot{V}_3 = \dot{V}_1 - e_\nu^T K_1 e_\nu \le 0. \tag{28}$$

Note that $\dot{V}_3 = 0$ only if $e_\eta = 0$ and $e_\nu = 0$, which implies the convergence of the tracking error e_η and the velocity error e_ν to zero as well as the boundedness of the weight error $\tilde{W}$.

Thus the proof of the stability for the adaptive NN controller is complete.

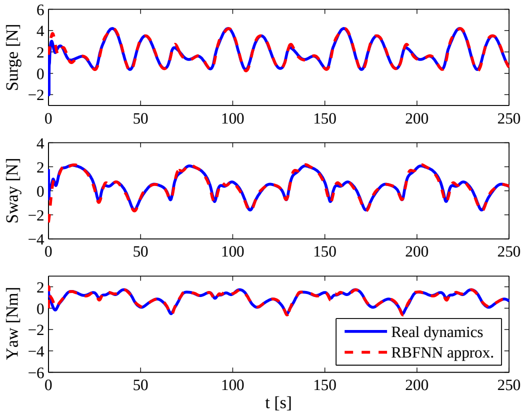

Fig. 5 Uncertain dynamic approximation.

4 Simulation Results

In this section, numerical simulations have been carried to evaluate the effectiveness of the proposed adaptive NN controller. We chose the vessel model—CyberShip II as the test bed of the controller. The CyberShip II is a replica of a supply ship in NTNU. It has a mass of 23.8 kg with a length of 1.255 m. More information about the model is given in detail in [20].

4.1 Trajectory tracking experiment

Table 1 Constructive parameters of the RBFNN

Symbols	Values	Description
m	9	Number of input nodes
n	1000	Number of hidden nodes
p	3	Number of output nodes
μ	[-1,1]	Center of Gaussian function
σ	10	Width of Gaussian function
Θ	I_{1000}	Weight update rate

The dynamic parameters for the ship model are given as:

$$M = \begin{bmatrix} 25.8 & 0 & 0 \\ 0 & 24.661 & 1.095 \\ 0 & 1.095 & 2.76 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 0 & -24.661v - 1.095r \\ 0 & 0 & 25.8u \\ 24.661v + 1.095r & -25.8u & 0 \end{bmatrix}$$

and $D = [d_{11}\ 0\ 0; 0\ d_{22}\ d_{23}; 0\ d_{32}\ d_{33}]$, where

$$\begin{aligned} d_{11} &= 0.7225 + 1.3274|u| + 5.8664u^2 \\ d_{22} &= 0.8612 + 36.2823|v| + 8.05|r| \\ d_{23} &= -0.1079 + 0.845|v| + 3.45|r| \\ d_{32} &= -0.1052 - 5.0437|v| - 0.13|r| \\ d_{33} &= 1.9 - 0.08|v| + 0.75|r|. \end{aligned}$$

To simulate the trajectory tracking task for fine maneuvering, we chose a complex reference trajectory in limited space. The reference trajectory is defined as:

$$\begin{aligned} x_d &= 3\sin(0.1t)(1 - \sin(0.1t)) \\ y_d &= 3\cos(0.1t) \\ \psi_d &= tan^{-1}(\frac{\dot{y}_d}{\dot{x}_d}) \end{aligned}$$

The initial position of the vessel is placed at $[2, 3, -180°]$. We assume there exist environmental disturbances, which are set as:

$$\Delta = \begin{bmatrix} 1 + 0.1\sin(0.2t) + 0.3\sin(0.4t) + 0.3\cos(0.2t) \\ 1 + 0.1\sin(0.2t) + 0.2\sin(0.1t) - 0.1\cos(0.4t) \\ 1 + 0.1\sin(0.2t) - 0.3\sin(0.4t) - 0.5\cos(0.4t). \end{bmatrix}$$

In the simulation, the design parameters of the controller are chosen as $K_0 = 0.3I_3$ and $K_1 = 12I_3$. A RBFNN was constructed to approximate the uncertain dynamics. Table 1 lists the parameters of the RBFNN. Note that the inputs of the RBFNN are normalized before function approximation. The overall weight $\hat{W}$ of the RBFNN was initially set to zero. The centers of the Gaussian functions are evenly spaced over the input space. For each input dimension, there are more than two Gaussian functions ($1000 > 2^9$). Therefore, function approximation ability can be guaranteed.

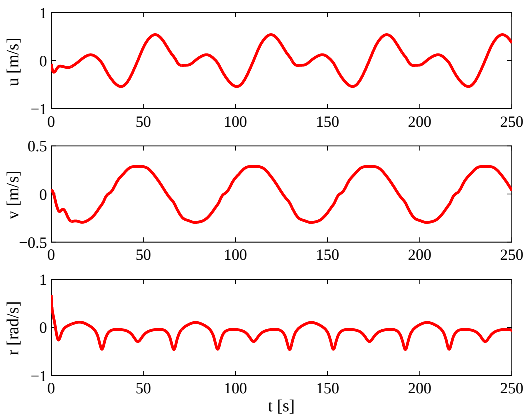

Fig. 6 Tracking velocities.

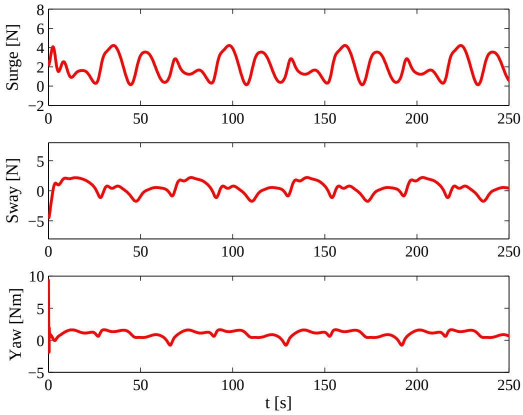

Fig. 7 Surge control force, sway control force and yaw control torque.

The tracking result is depicted in Fig. 4. It can be seen that the vessel tracks the reference trajectory smoothly and accurately under the time-varying disturbances. Fig. 5 shows how the RBFNN approximates the uncertain dynamics of the vessel. From the figure, it is clearly observed that the RBFNN can fast and precisely approach the real dynamics of (21) in a short period of time, which in turn validates the rapidly exponentially convergence of tracking error and velocity error and the boundedness of estimation error. Fig. 6 shows the curves of the surge velocity, the sway velocity and the yaw rate vary with respect to time. The corresponding control inputs including the surge force, the sway force and the yaw torque are shown in Fig 7. Considering the scaled version of the ship model, the results are smooth and reasonable. As a result, the proposed adaptive NN controller really provides good tracking behavior.

4.2 Control parameter analysis

As described in Section 3, the adaptive NN controller can be affected by the control gain K_0 and K_1, as well as the parameters that are involved in the RBFNN. Here, we investigate how they affect the tracking performance. To quantitatively analyze the impact of each control parameter, only one parameter is tuned within an acceptable range while the other parameters are fixed to the values that are shown in Section 4.1.

4.2.1 Control gain K_0 & K_1

From Fig. 3, it can be seen the control gain K_0 affects the tracking performance indirectly by modifying the inputs of the RBFNN. Fig. 8 illustrates the comparison of tracking performance for different scaling of K_0. From the top figure, it is observed that with the growth of K_0, both the transient period and the steady-state tracking error decrease. But the corresponding initial forces/torque τ from the bottom figure increase exponentially. Furthermore, the oscillation of forces/torque

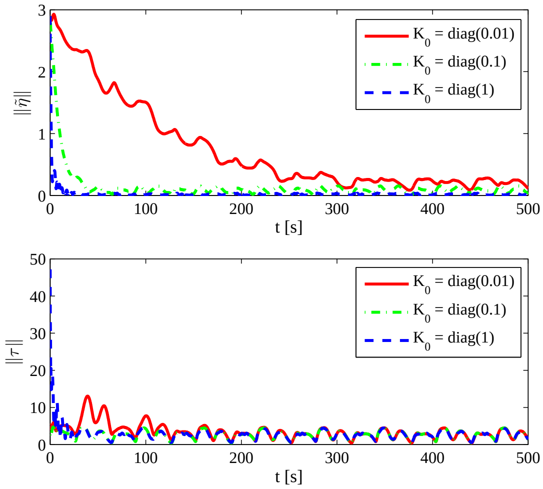

Fig. 8 The variation of tracking performance by scaling K_0. Top: norm of tracking error. Bottom: norm of resultant force/torque.

during the transient period increases dramatically, which is of low practicability and maneuverability for real applications. Further increasing K_0 is meaningless since the resultant forces/torque is beyond the saturation limits of the ship model. An intuitive tuning of K_0 is suggested between $[0.1I_3, 0.4I_3]$.

A similar scaling of the control gain K_1 is shown in Fig. 9. Although K_1 has a direct impact on the resultant forces/torque τ, modifying K_1 will not change the transient period and the magnitude of forces/torque so much. If K_1 is small, e.g. $K_1 \leq 5I_3$, the resultant forces/torque τ will be always insufficient, resulting in an inferior tracking performance. But when K_1 is large enough, e.g. $K_1 \geq 10I_3$, continuously increasing K_1 will not affect the steady-state tracking error at all. Similar to K_0, the growth of K_1 leads to the growth of the corresponding initial forces/torque. To simulate fine maneuvering in a realistic manner, K_1 is suggested to choose within $[10I_3, 20I_3]$.

4.2.2 Control parameters in the RBFNN

The tracking performance is also sensitive to the control parameters in the RBFNN. As mentioned before, the number of hidden nodes n in RBFNN determines how accurate the RBFNN is to approximate unknown nonlinear functions. Therefore, changing the number of hidden nodes in RBFNN will definitely affect the tracking performance. From Fig. 10, increasing n has no impact on the tracking performance except the steady-state tracking error. A larger number of n results in a lower steady-state tracking error. However, continuously increasing n cannot significantly decrease the steady-state tracking error but brings more computational complexity. Therefore, in the simulation, tuning n to 1000 could be a good trade-off between the steady-state tracking error and the computational complexity.

The update rate Θ is another impact factor of the tracking performance, as shown in Fig. 11. From the top graph of Fig. 11, increasing Θ mainly affects the steady-state tracking error. A higher value of Θ leads to a lower steady-state

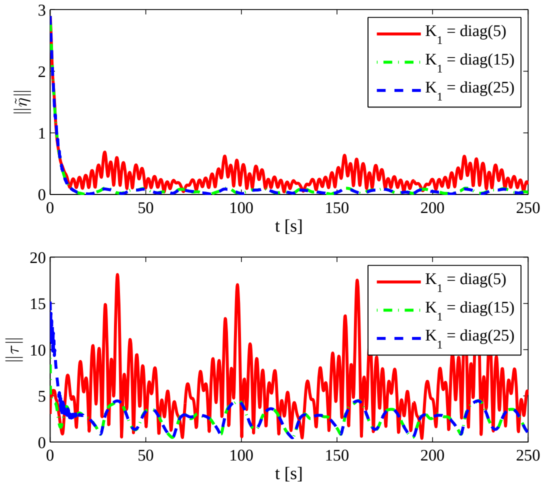

Fig. 9 The variation of tracking performance by scaling K_1. Top: norm of tracking error. Bottom: norm of resultant force/torque.

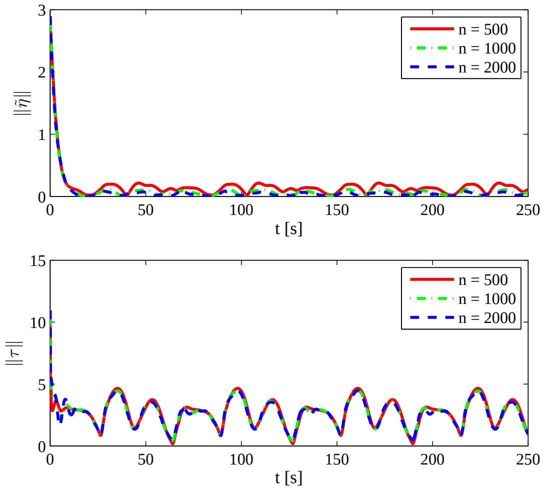

Fig. 10 The variation of tracking performance by scaling hidden nodes n in the RBFNN. Top: norm of tracking error. Bottom: norm of resultant force/torque.

tracking error. However, combined with the bottom graph of Fig. 11, continuously increasing Θ has a little improvement for the tracking error, but gives rise to extra oscillation on the resultant forces/torque. To avoid this happens, Θ is suggested to be around I_{1000}.

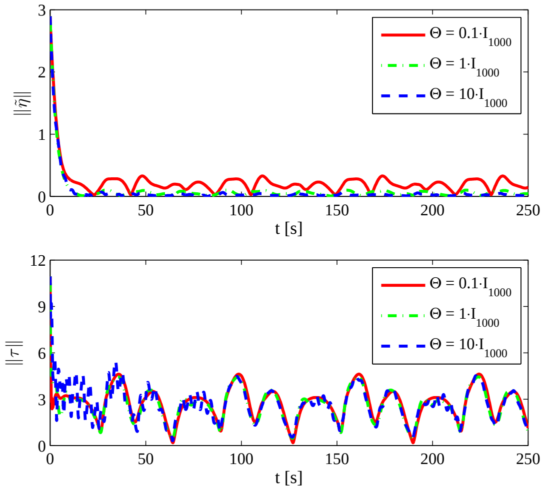

Fig. 11 The variation of tracking performance by scaling the update rate Θ in the RBFNN. Top: norm of tracking error. Bottom: norm of resultant force/torque.

4.3 Tracking performance comparison

This experiment compares the tracking performance of the proposed adaptive NN controller with a PID controller using acceleration feedback [2] and a single-layer NN controller [15]. Both the PID controller and the single-layer NN controller are performed the experiment in Section 4.1, i.e., to force the ship model to track the same reference trajectory under the same environmental disturbances.

Because the resultant forces and torque must further distribute to all of the thrusters on the vessel, it is necessary to reduce the magnitude of forces and torque to avoid achieving the saturation limit. Hence, we take the magnitude of forces and torque into consideration and design the system error of the controller as a function of tracking error and corresponding forces and torque:

$$\|\zeta\| = \sqrt{\|\tilde{\eta}\| \cdot \|\tau\|}. \tag{29}$$

In this way, a low system error indicates that the controller only needs to provider low forces and torque to maintain an acceptable tracking error. Fig. 12 shows the comparison results of tracking performance between these controllers. All of them can make the ship model follow the desired trajectory under an acceptable system error. The PID controller needs a nontrivial tuning of the PID gains to obtain a lower system error value. Even we manage that, the result shows it has the highest error value at the beginning and an oscillating transient performance before achieving steady state. The single-layer NN controller performs better than the PID controller but has a higher initial system error value as well as a slower decay of system error than the proposed adaptive NN controller. This is because the adaptive NN controller contains an additional nonlinear basis functions of layer that can approximate nonlinear functions more efficiently. From the result, we conclude that the proposed adaptive NN controller is effective for fine trajectory tracking.

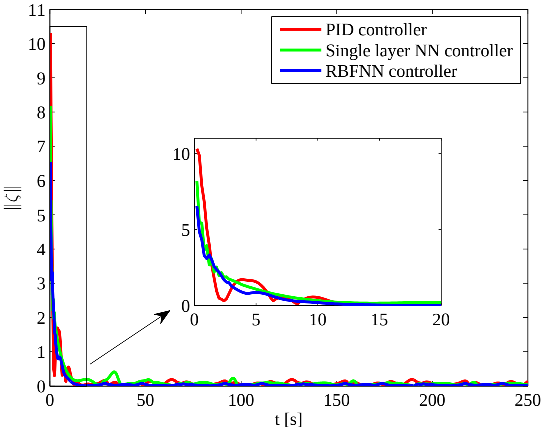

Fig. 12 Comparison of tracking performance.

5 Discussion

Here we discuss about the key role of the RBFNN in the proposed controller, as well as the limitation of the controller in real applications.

As shown in Section 3, the control law in (22) is consisted of two parts: the estimated dynamic by the RBFNN and the proportional control of velocity error. At the beginning, the RBFNN has no output due to the zero values of the initial weights. The proportional control of velocity error is thus dominant to the control law. Later, as the online learning of the RBFNN and the decrease of the velocity error, the proportional part will decrease whereas the learned dynamic part would be in charge of the control law. Therefore, if only the proportional control of velocity error is used without the RBFNN, the tracking task will fail.

Regarding the limitation of the controller, it is closely related to the assumptions we have made in Section 3. First, if the noise of sensor data exists, it will affect the control law, the updating law, the input vector of the RBFNN, and consequently affect the tracking performance. The test of sensor noise is beyond this paper, but in principle, using Kalman filter technique and some sensor fusion algorithms can reduce the impact of sensor noise on tracking performance to some extent. Second, the controller is not applicable for trajectory tracking in severe environmental conditions. Because the environmental disturbance changes more irregularly. However, for most offshore operation applications, including fine maneuvering, tasks are performed in calm weather. Therefore, the NN-based controller is competent to tasks in that case. Third, to achieve high tracking accuracy, the desired trajectories are required to be sufficiently smooth. According to (7), (15) and the input vector of the RBFNN, both $\dot{\eta}_d$ and $\ddot{\eta}_d$ should be continuous and bounded. Actually, smooth trajectory can avoid actuator saturation induced by sudden jumps of tracking errors. We have tested the controller with different types of trajectories, such as the elliptic trajectory and the octomorphic trajectory. The results show good tracking performance for smooth trajectories but inferior performance for non-smooth ones due to discontinuous command inputs. To sum up, the controller is suitable for fine maneuvering with smooth trajectory in calm weather, as long as sensor noises are eliminated.

6 Conclusion

In this paper, an adaptive NN controller has been designed for fine maneuvering of surface vessels applying on offshore applications. Taking advantages of function approximating ability of NN, the proposed controller can achieve online learning control of trajectory tracking with unknown dynamics of the vessel and uncertain environmental disturbances. Through the backstepping technique and Lyapunov stability analysis, the controller is proved stable and guaranteed to converge tracking errors to zero. Trajectory tracking simulation and its performance studies are carried out by using the CyberShip II ship model as the test bed. From the results, it confirms the effectiveness of the controller for providing good transient and steady state performance in fine trajectory tracking.

Future work will be focused on twofold: (1) Design hierarchical control for fine maneuvering from path planning to final thrust allocation, taking into consideration all the constraints such as power consumption and thruster's features and capabilities; (2) Develop a training and evaluation system regarding to fine maneuvering for nautical certification.

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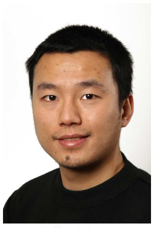

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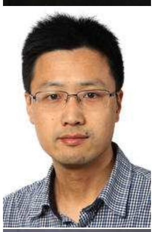

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