Expert Systems with Applications 40 (2013) 1629–1635

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

An efficient neural network approach to tracking control of an autonomous surface vehicle with unknown dynamics

Chang-Zhong Pan [a,b,c], Xu-Zhi Lai [a,b,*], Simon X. Yang [c], Min Wu [a,b]

[a] School of Information Science and Engineering, Central South University, Changsha, Hunan 410083, China
[b] Hunan Engineering Laboratory for Advanced Control and Intelligent Automation, Changsha, Hunan 410083, China
[c] Advanced Robotics and Intelligent Systems (ARIS) Laboratory, School of Engineering, University of Guelph, Guelph, Ontario, Canada N1G 2W1

ARTICLE INFO

Keywords:
Autonomous surface vehicles
Robots
Unknown dynamics
Tracking control
Neural networks
Lyapunov stability

ABSTRACT

This paper proposes an efficient neural network (NN) approach to tracking control of an autonomous surface vehicle (ASV) with completely unknown vehicle dynamics and subject to significant uncertainties. The proposed NN has a single-layer structure by utilising the vehicle regressor dynamics that expresses the highly nonlinear dynamics in terms of the known and unknown dynamic parameters. The learning algorithm of the NN is simple yet computationally efficient. It is derived from Lyapunov stability analysis, which guarantees that all the error signals in the control system are uniformly ultimately bounded (UUB). The proposed NN approach can force the ASV to track the desired trajectory with good control performance through the on-line learning of the NN without any off-line learning procedures. In addition, the proposed controller is capable of compensating bounded unknown disturbances. The effectiveness and efficiency are demonstrated by simulation and comparison studies.

1. Introduction

An autonomous surface vehicle (ASV) is also called an unmanned surface vessel (USV), which can operate on the surface of lakes, rivers and oceans. Over the past few years, there has been renewed interest in the development of ASVs, see Benjamin and Curcio (2004), Caccia et al. (2007), Desa et al. (2007), Martins, Almeida, Silva, and Pereira (2006) and Xu, Chudley, and Sutton (2006) for example. Due to their emerging applications in commercial, civilian and military missions (Størkersen, Kristensen, Indreeide, Seim, & Glancy, 1998), the control of ASVs has become an intensive research area. However, how to control the ASVs efficiently is still very challenging, which might stem from the fact that (Fossen, 2002): (1) it is hard to use current modelling techniques to obtain an accurate vehicle dynamic model, which is generally highly nonlinear, time-varying, and coupled in nature; and (2) the operation environment of marine vehicles is usually very complex and unstructured, which brings unpredictable perturbations to the control system, such as ocean currents, waves and wind.

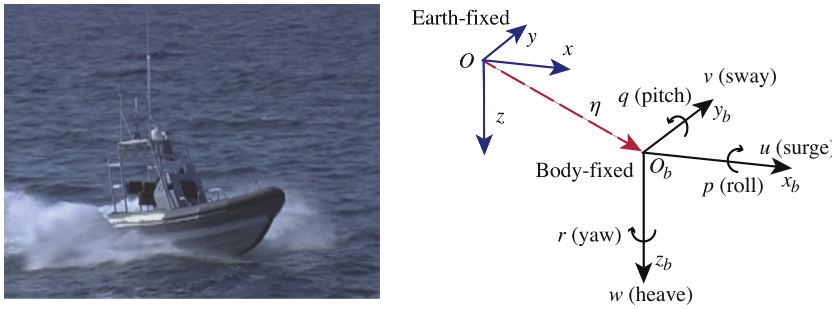
Basic control problems of surface vehicles are classified into point stabilisation (Liu, Yu, & Zhu, 2011), way-point manoeuvring (Fredriksen & Pettersen, 2006), path following (Almeida, Silvestre, & Pascoal, 2007; Bibuli, Bruzzone, & Caccia, 2009), trajectory tracking (Zou, Chen, Feng, & Liu, 2011), and formation control (Peng, Wang, Chen, Hu, & Lan, 2012). Many control approaches have been proposed in the literature, such as conventional PID control, nonlinear recursive/adaptive control, sliding-mode control (SMC), and intelligent control. PID control is very simple and easy to understand. But due to the complexities of the surface vehicles, the designed controllers (Escario, Jimenez, & Giron-Sierra, 2012; Fossen, 2002; Moreira, Fossen, & Guedes Soares, 2007) may cause poor control performance. In addition, the PID tuning is still a difficult problem, even though there are only three parameters.

To improve the system control performance, nonlinear controllers that usually employ Lyapunov method, recursive backstepping technique, or adaptive control have been widely proposed. For example, with the aid of Lyapunov's direct method, Jiang (2002) designed two systematic tracking controllers for an underactuated ship. Based on backstepping technique, Du and Guo (2004) established an uncertain nonlinear mathematical model and designed a nonlinear adaptive controller for the course-tracking control. Aguiar and Hespanha (2007) presented an adaptive switching supervisory control combined with a nonlinear Lyapunov-based tracking control law. The controllers using SMC have low sensitivity to plant parameter variations and disturbances. They can also greatly improve the system control performance. For instance, Cheng, Yi, and Zhao (2007) proposed a multi-variable sliding mode control law for the trajectory tracking of a ship, where the positions and yaw angle were simultaneously tracked. Ashrafiuon

* Corresponding author at: School of Information Science and Engineering, Central South University, Changsha, Hunan 410083, China. Tel./fax: +86 731 88836091.

E-mail address: xuzhi@csu.edu.cn (X.-Z. Lai).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.09.008



(a) (b)

Fig. 1. (a) An ASV; (b) definition of coordinate frames.

and McNinch (2008) presented a sliding-mode control law for trajectory tracking of underactuated ASVs, where straight-line and circular trajectories were accurately tracked. However, both the nonlinear controllers and SMC controllers lie in the model-based approaches. They require the accurate dynamic model of the vehicle, which is almost impossible in practise. Although many advanced modelling and identification techniques (Caccia, Bruzzone, & Bono, 2008; Iseki & Ohtsu, 2000; Park, Ohtsu, & Kitagawa, 2000; Wu, Peng, Ohtsu, Kitagawa, & Itoh, 2012) can be employed to accomplish the model-based controllers design, it is still very hard to obtain an accurate description of the vehicle.

Intelligent control including fuzzy control and neural network (NN) has shown to be powerful in controller design for uncertain dynamical systems (Chen, Lin, & Chen, 2008; Peng & Dubay, 2012; Soyguder, 2011). In comparison with model-based approaches, fuzzy control and NN control are considered as approximation-based methods, which do not require parametric or functional certainty. Velagic, Vukic, and Omerdic (2003) used fuzzy control for track keeping of a surface ship. Yang, Zhou, and Ren (2003) proposed a robust fuzzy-based model reference adaptive control (MRAC) for course keeping using full-state information. Rigatos and Tzafestas (2006) proposed an adaptive fuzzy H_∞ control for the ship steering problem, which could keep the influence of the modelling errors and the external disturbances on the tracking error below an arbitrary desirable level. Seo, Park, Lee, and Wang (2009) also applied a fuzzy control model to the steering control system based on linguistic instruction. However, fuzzy rules are mainly obtained by trial and error from the knowledge and experience of domain experts, which are always not available. Moreover, a large set of rules requires more computation time.

Since NN has an inherent ability of learning nonlinear dynamics, it is attractive to apply it to the control of surface vehicles (Burns, 1995; Chen, Ge, & Choo, 2009; Dai, Wang, & Luo, 2012; Tee & Ge, 2006; Zhang, Hearn, & Sen, 1996, 2011). One of the important advantages of using NN is that the dynamics of the vehicles do not need to be completely known as a prior condition. This is a very desirable feature in the design of the controller. Unfortunately, most of the existing literature used multi-layer neural networks, such as back propagation (BP) and radial basis function (RBF) NN, to approximate the nonlinear dynamics, which makes the control algorithm very complicated. In this paper, we focus on developing an efficient neural network control approach for the real-time tracking control of an ASV, which only employs a single-layer structure.

In the proposed approach, a velocity controller is first derived from the vehicle kinematic level to guarantee the asymptotic stability of the global tracking error. Then, using backstepping technique, the controller is extended to the dynamic case, where real-time NN-based control force is generated to drive the actual vehicle velocity to converge to the desired real-time velocity. There are three parts in the proposed controller: one part from a feedback control to guarantee the global stability of the vehicle; the second part from a NN to achieve real-time tracking control through its on-line learning ability; and the third part from a robust compensator to suppress the influence of the bounded unknown disturbance. With a known vehicle architecture, the dynamics parameters of the ASV, such as mass, moment of inertia, hydrodynamic and damping coefficients, are assumed to be completely unknown. By utilising the regressor dynamics formulation that expresses the nonlinear vehicle dynamics in terms of the known and unknown dynamic parameters, the proposed NN is employed with only a single-layer structure. No off-line learning procedures are needed for the NN. The system stability and convergence of the tracking error signals are rigorously proved using Lyapunov theory. The learning algorithm of the NN derived from stability analysis of a Lyapunov function candidate is much simpler than other most commonly used NN learning algorithm.

This paper is organised as follows. Section 2 introduces the mathematical model of an ASV and states the problem formulation. Section 3 presents the NN controller design. Section 4 presents the simulation and comparison studies. Finally, Section 5 concludes this paper.

2. Background and problem formulation

This section describes the kinematics and dynamics of an ASV. Some preliminaries and formulations are also presented.

2.1. Kinematics

An ASV is shown in Fig. 1(a), which requires six independent coordinates to determine its complete configuration (position and orientation). The six different motion components are conveniently defined as surge, sway, heave, roll, pitch, and yaw (see Fig. 1(b)). Assuming that the vehicle motions in heave, roll and pitch are neglected, two coordinate frames are defined to be the earth-fixed frame $\{O\}$ and the body-fixed frame $\{O_b\}$. Then, the kinematic equation of the ASV is given by

$$\dot{\eta} = J(\eta)v, \tag{1}$$

where

$$J(\eta) = \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

is the Jacobian transformation matrix; $\eta = [x, y, \phi]^\top \in \mathbb{R}^3$ is the vector including the positions and heading in the Earth-fixed frame; $v = [u, v, r]^\top \in \mathbb{R}^3$ is the vector including the surge, sway, and yaw velocities in the Body-fixed frame.

The posture of the vehicle in the Earth-fixed frame can be uniquely determined by the vector η. Assume that a reference path provides the desired posture $\eta_d = [x_d, y_d, \phi_d]^\top \in \mathbb{R}^3$, which is generated with the desired velocities u_d and r_d. Moreover, no sway velocity is desired, i.e., $v_d = 0$. The desired trajectory must satisfy

$$\dot{\eta}_d = \bar{J}(\eta_d)\bar{v}_d, \tag{3}$$

where $\bar{v}_d = [u_d, r_d]^\top \in \mathbb{R}^2$, and

$$\bar{J}(\eta_d) = \begin{bmatrix} \cos\phi_d & 0 \\ \sin\phi_d & 0 \\ 0 & 1 \end{bmatrix}. \tag{4}$$

Define the tracking error in the Earth-fixed frame to be $\eta_e(t) = \eta - \eta_d = [x_e, y_e, \phi_e]^\top \in \mathbb{R}^3$. Then, the error expressed in the Body-fixed frame $e_\eta(t) = [e_x, e_y, e_\phi]^\top \in \mathbb{R}^3$ is obtained using the global diffeomorphic coordinate transformation

$$e_\eta(t) = J^\top(\eta)\eta_e(t). \tag{5}$$

The error dynamics in the Body-fixed frame is given by

$$\dot{e}_\eta(t) = \begin{bmatrix} u + re_y - u_d\cos\phi_e \\ v - re_x + u_d\sin\phi_e \\ r - r_d \end{bmatrix}. \tag{6}$$

2.2. Dynamics

The nonlinear dynamics of the ASV is given by (Fossen, 1994)

$$M\dot{v} + C(v)v + D(v)v + \tau_d = \tau, \tag{7}$$

where $M \in \mathbb{R}^{3\times3}$ is the inertia matrix (including the added mass), $C(v) \in \mathbb{R}^{3\times3}$ is the matrix of Coriolis and centrifugal terms, $D(v) \in \mathbb{R}^{3\times3}$ is the damping matrix, $\tau_d \in \mathbb{R}^3$ is the disturbance vector including unstructured and unmodelled dynamics, and $\tau = [\tau_1, \tau_2, \tau_3]^\top \in \mathbb{R}^3$ is the control force and moment acting on the vehicle in the Body-fixed reference frame. They have the structures as follows.

$$M = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix},$$

$$C(v) = \begin{bmatrix} 0 & 0 & -m_{22}v - m_{23}r \\ 0 & 0 & m_{11}u \\ m_{22}v + m_{32}r & -m_{11}u & 0 \end{bmatrix},$$

$$D(v) = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & d_{23} \\ 0 & d_{32} & d_{33} \end{bmatrix}.$$

In real applications, it is impossible to obtain accurate physical parameters for the dynamics (7), which means that M, $C(v)$ and $D(v)$ are at least partially unknown. To facilitate the subsequent control development, the dynamic model is written into a linear form using the regressor dynamics formulation:

$$Y(v,\dot{v})\theta + \tau_d = \tau, \tag{8}$$

$$Y(v,\dot{v})\theta = M\dot{v} + C(v)v + D(v)v, \tag{9}$$

where $\theta \in \mathbb{R}^r$ is a vector consisting of all the vehicle parameters that are often imperfectly known and difficult to determine, such as masses, moments of inertia, friction coefficients, etc.; $Y(v,\dot{v}) \in \mathbb{R}^{3\times r}$ is a measurable regression matrix consisting of the known functions of the robot velocity v and acceleration $\dot{v}$; r is the number of the known and unknown robot dynamics parameters.

The dynamics of (7) preserves the following properties (Fossen, 2002):

Property 1. *The inertia matrix M is symmetric positive definite.*

Property 2. *The Coriolis and centripetal matrix $C(v)$ is skew-symmetric.*

Property 3. *The matrix $\dot{M} - 2C(v)$ is skew-symmetric.*

Property 4. *The hydrodynamic damping matrix $D(v)$ is positive definite.*

In addition, the following assumptions are made.

Assumption 1. The external disturbances are bounded by positive real value δ, i.e.,

$$\|\tau_d\| \leqslant \delta. \tag{10}$$

Assumption 2. For all $t > 0$, there exist positive constants λ_1 and λ_2 such that $\|\dot{\eta}_d(t)\| \leqslant \lambda_1$ and $\|\ddot{\eta}_d(t)\| \leqslant \lambda_2$.

Assumption 1 is reasonably made for the design of a robust compensator. Assumption 2 requires that the desired trajectory should be sufficiently smooth to avoid actuator saturation induced by sudden jumps of tracking error due to discontinuous command inputs.

Control problem: Consider the ASV described by (1) and (7) with unknown dynamics M,$C(v)$,$D(v)$ and bounded disturbance τ_d. Design a NN-based control force τ with a computationally efficient learning law to drive the ASV to track a given smooth desired trajectory η_d, ensuring that all the tracking error signals are bounded in a small neighbourhood of zero.

3. Controller design

In this section, the controller is first derived at the kinematic level by assuming that the velocity of the vehicle is the control signal. Then the controller is extended to the dynamic case where the force τ should be the real control input. Since no knowledge of dynamics of the vehicle is known, a single-layer NN is finally proposed to approximate the unknown dynamics.

3.1. Kinematic controller

At the kinematic level, the objective is to derive a velocity control signal v_c that drives the steering system (1) to precisely track the reference trajectory η_d.

Consider the Lyapunov function candidate V_1 for the tacking error e_η

$$V_1 = \frac{1}{2}e_\eta^\top e_\eta. \tag{11}$$

From (5) and (6), the time derivative of the Lyapunov function becomes

$$\dot{V}_1 = e_x(u - u_d\cos e_\phi + re_y) + e_y(v + u_d\sin e_\phi - re_x) + e_\phi(r - r_d). \tag{12}$$

If the velocity $v = [u, v, r]^\top$ is made to follow the command signal $v_c = [u_c, v_c, r_c]^\top$ given by the feedback law

$$v_c = \begin{bmatrix} -k_1e_x + u_d\cos e_\phi \\ -k_2e_y + u_d\sin e_\phi \\ -k_3e_\phi + r_d \end{bmatrix}, \tag{13}$$

where k_1, k_2 and k_3 are positive constants. Then,

$$\dot{V}_1 = -k_1 e_x^2 - k_2 e_y^2 - k_3 e_\phi^2 = -e_\eta^\top K_1 e_\eta \leqslant 0, \tag{14}$$

where $K_1 = \mathrm{diag}\{k_1, k_2, k_3\}$ is positive definite. Note that $\dot{V}_1 = 0$ if and only if $e_x = 0$, $e_y = 0$, and $e_\phi = 0$, therefore, the error system (6) under the control law (13) is asymptotically stable.

3.2. Dynamic controller

The dynamic controller is used to generate real-time control force τ to drive the actual velocity to converge to the desired velocity. Since M,$C(\nu)$ and $D(\nu)$ are always uncertain and unknown, a single-layer NN is employed to approximate them.

Following the methodology of backstepping, let ν be the virtual control inputs, and ν_c be the corresponding virtual control law. Define the auxiliary error variable as

$$e_c = \nu_c - \nu. \tag{15}$$

Taking its time derivative and using (7) yields

$$M\dot{e}_c = -\tau - D_2 e_c + [M\dot{\nu}_c + C(\nu)\nu + D(\nu)\nu_c] + \tau_d. \tag{16}$$

As stated in Section 2, all the unknown dynamics parameters are lumped in a vector θ, i.e.,

$$\theta = [m_{11}, m_{22}, m_{23}, m_{33}, d_{11}, d_{22}, d_{23}, d_{32}, d_{33}]^\top \in \mathbb{R}^9.$$

Define

$$Y(\xi)\theta = M\dot{\nu}_c + C(\nu)\nu + D(\nu)\nu_c, \tag{17}$$

where $Y(\xi) \in \mathbb{R}^{3\times 9}$is the measurable regression matrix, i.e.,

$$Y(\xi) = \begin{bmatrix} \dot{u}_c & -vr & 0 & 0 & u_c & 0 & 0 & 0 & 0 \\ uv & \dot{v}_c & \dot{r}_c & 0 & 0 & v_c & r_c & 0 & 0 \\ -uv & uv & \dot{v}_c & \dot{r}_c & 0 & 0 & 0 & v_c & r_c \end{bmatrix}, \tag{18}$$

which can be computed through the measured signal vector ξ

$$\xi = \left[\nu^\top, \nu_c^\top, \dot{\nu}_c^\top\right]^\top. \tag{19}$$

Then, Eq. (16) becomes

$$M\dot{e}_c = -\tau - D(\nu)e_c + Y(\xi)\theta + \tau_d. \tag{20}$$

A suitable control input for the velocity is given by the computed force:

$$\tau = K_c e_c + \tau_{\mathrm{nn}} - \gamma, \tag{21}$$

where K_c is a diagonal positive definite gain matrix, γ is a robust term to compensate the unmodelled unstructured disturbances, and τ_{nn} is the output force from a single-layer neural network, which is given by

$$\tau_{\mathrm{nn}} = Y(\xi)W, \tag{22}$$

where $W \in \mathbb{R}^9$ represents the connection weights of the neural network, which is also an approximation of θ. The input of the neural network is the regressor $Y(\xi)$. Substituting (21) into (20) yields the closed-loop error dynamics

$$M\dot{e}_c = -(K_c + D(\nu))e_c + Y(\xi)\tilde{\theta} + \gamma + \tau_d, \tag{23}$$

where

$$\tilde{\theta} = \theta - W, \tag{24}$$

which is the estimate error of θ. Therefore, the dynamic controller for the ASV consists of (21) and (22).

Next, it shows how to choose an efficient learning algorithm and a robust compensator as well for the neural network to guarantee that the control system is stable and the tracking error and other error signals are bounded. To this end, the following theorem is presented.

Theorem 1. *Consider the ASV represented by (1) and (7). If the force control τ is designed as (21) and (22) with the learning law and the robust term as*

$$\dot{W} = \Gamma Y^\top(\xi)e_c + K_\theta\tilde{\theta}, \tag{25}$$

$$\gamma = -k_d - e_c + e_\eta, \tag{26}$$

where $\Gamma \in \mathbb{R}^{r\times r}$ is a positive constant design matrix, and $\|k_d\| \geqslant \delta$. Then, the stability of the control system is guaranteed, and all the tracking error signals converge asymptotically to a small neighbourhood of zero.

Proof. Consider the Lyapunov function candidate V augmented from V_1

$$V = V_1 + \frac{1}{2}\left(e_c^\top M e_c + \tilde{\theta}^\top\Gamma^{-1}\tilde{\theta}\right), \tag{27}$$

Obviously, $V = 0$ if and only if $e_\eta = 0$, $e_c = 0$ and $\tilde{\theta} = 0$. Taking the time derivative of (27) and using (15) yields

$$\begin{aligned} \dot{V} &= \dot{V}_1 - e_c^\top e_\eta + \frac{1}{2}\dot{e}_c^\top M e_c + \frac{1}{2}e_c^\top \dot{M} e_c + \frac{1}{2}e_c^\top M\dot{e}_c + \tilde{\theta}^\top\Gamma^{-1}\dot{\tilde{\theta}} \\ &= \dot{V}_1 - e_c^\top e_\eta + \frac{1}{2}e_c^\top\dot{M}e_c + \frac{1}{2}[M\dot{e}_c]^\top e_c + \frac{1}{2}e_c^\top[M\dot{e}_c] + \tilde{\theta}^\top\Gamma^{-1}\dot{\tilde{\theta}}. \end{aligned} \tag{28}$$

Substituting (23) into the above equation obtains

$$\begin{aligned} \dot{V} &= \dot{V}_1 - e_c^\top e_\eta + \frac{1}{2}e_c^\top[\dot{M} - 2C(\nu)]e_c - e_c^\top K_c e_c + \tilde{\theta}Y^\top(\xi)e_c \\ &\quad + \tilde{\theta}^\top\Gamma^{-1}\dot{\tilde{\theta}} + e_c^\top\tau_d + e_c^\top\gamma \\ &= \dot{V}_1 - e_c^\top e_\eta + \frac{1}{2}e_c^\top[\dot{M} - 2C(\nu)]e_c - e_c^\top K_c e_c + \tilde{\theta}^\top[Y^\top(\xi)e_c \\ &\quad + \Gamma^{-1}\dot{\tilde{\theta}}] + e_c^\top\tau_d + e_c^\top\gamma. \end{aligned} \tag{29}$$

Since $\dot{M} - 2C(\nu)$ is skew-symmetric, and the robust term γ is chosen as (26), then Eq. (29) becomes

$$\begin{aligned} \dot{V} &= \dot{V}_1 - e_c^\top K_c e_c + \tilde{\theta}^\top[Y^\top(\xi)e_c + \Gamma^{-1}\dot{\tilde{\theta}}] - e_c^\top e_c + e_c^\top(\tau_d - k_d) \\ &\leqslant \dot{V}_1 - e_c^\top K_c e_c + \tilde{\theta}^\top[Y^\top(\xi)e_c + \Gamma^{-1}\dot{\tilde{\theta}}] - e_c^\top e_c + \|e_c\|(\|k_d\| - \delta) \end{aligned} \tag{30}$$

If choose

$$Y^\top(\xi)e_c + \Gamma^{-1}\dot{\tilde{\theta}} = -K_\theta\tilde{\theta}, \tag{31}$$

i.e.,

$$\dot{\tilde{\theta}} = -\Gamma Y^\top(\xi)e_c - K_\theta\tilde{\theta}, \tag{32}$$

where K_θ is a diagonal positive definite gain matrix. Then, $\dot{V}$ satisfies

$$\dot{V} \leqslant \dot{V}_1 - e_c^\top(K_c + I_3)e_c - \tilde{\theta}^\top K_\theta\tilde{\theta} + \|e_c\|(\|k_d\| - \delta) \leqslant \alpha V + \beta, \tag{33}$$

with

$$\alpha = \min\left(2\lambda_{\min}(K_1), \frac{2\lambda_{\min}(K_c + I_3)}{\lambda_{\max}(M)}, \frac{2\lambda_{\min}(K_\theta)}{\lambda_{\max}(\Gamma^{-1})}\right), \tag{34}$$

$$\beta = \|e_c\|(\|k_d\| - \delta), \tag{35}$$

where $\lambda_{\min}$ and $\lambda_{\max}$ denote the minimum and maximum eigenvalues; $\|A\|$ stands for the Euclidean norm of vector A. Note that β is bounded under Assumption 1 and the definition of V in (27), which can be made very small by appropriately choosing k_d in (26).

Therefore, it is straightforward to follow from the Comparison Lemma (Khalil, 1996) that

$$V \leqslant V(0)e^{-\alpha t} + \frac{\beta}{\alpha}, \quad t \geqslant 0, \tag{36}$$

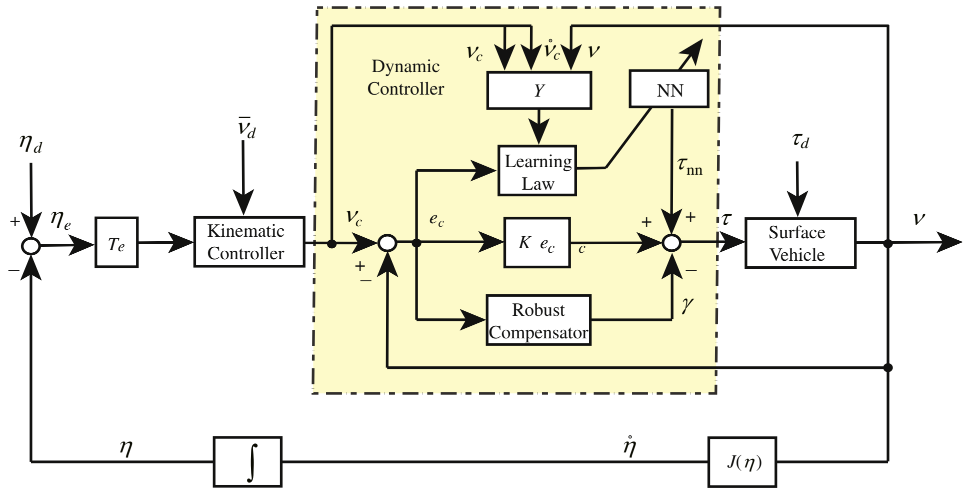


Fig. 2. Block diagram of the proposed NN-based control system.

from which we can further conclude that the control system error signals e_η, e_c and $\tilde{\theta}$ are uniformly ultimately bounded (UUB), and the tracking error converges asymptotically to the compact set $\Phi = \left\{e_\eta \in \mathbb{R}^3 | \|e_\eta\| \leqslant \sqrt{2\beta/\alpha}\right\}$.

On the other hand, since $\tilde{\theta} = \theta - W$, $\dot{\tilde{\theta}} = -\dot{W}$. From (32), the learning law for the neural network is obtained as

$$\dot{W} = \Gamma Y^\top(\xi)e_c + K_\theta \tilde{\theta}. \tag{37}$$

This completes the proof of Theorem 1. □

The block diagram of the proposed controller is shown in Fig. 2. In the proposed approach, two controllers including a kinematic controller and a dynamic controller are designed to achieve the real-time tracking control. The kinematic controller is employed to generate a desired velocity control signal v_c, which is used as the input for the dynamic controller. The dynamic controller is to generate the real-time control force τ for the ASV, which consists of three parts: τ_{nn} from the single-layer NN, $K_c e_c$ from the feedback control, and γ from the robust compensator. The learning algorithm of the NN is derived from the Lyapunov stability analysis.

Remark 1. In many literature, e.g. Chen et al. (2009), Dai et al. (2012) and Zhang et al. (1996, 2011), the control methods used back propagation (BP), radial basis function (RBF) or adaptive feedback-feedforward based neural networks to approximate the unknown nonlinear dynamics. All of these NNs have multi-layer structures, and the NN learning algorithms are quite expensive. In our control approach, however, a single-layer NN is proposed by taking advantage of the regressor dynamics formulation (17), which expresses the nonlinear dynamics in a linear form in terms of the known and unknown dynamic parameters. Notice that the learning law (37) is simple and no off-line learning phase is required. More interestingly, by choosing $K_\theta = 0$, the learning law (37) can be further written as

$$\dot{W} = \Gamma Y^\top(\xi)e_c, \tag{38}$$

which becomes much simpler, and computationally more efficient.

4. Numerical simulations

To illustrate the performance and effectiveness of the proposed control approach, numerical simulations and comparisons are performed for the ASV with no knowledge of the vehicle dynamics.

The vehicle model is briefly described in Section 2, and the vehicle data comes from the ship Cybership 2, a 1:70 scale model of a supply vessel, which has a mass of $m = 23.8$ kg and a length of $L = 1.255$ m. For detail parameters, the readers are refereed to Tee and Ge (2006), Dai et al. (2012).

4.1. Simulation results of tracking an ellipse

The reference trajectory is defined as an ellipse given by

$$x_d = 15\sin(0.1t),$$
$$y_d = 10\cos(0.1t),$$

with time-varying desired velocities $u_d = \sqrt{\dot{x}_d^2 + \dot{y}_d^2}$, $r_d = 0.15/(\dot{x}_d^2 + \dot{y}_d^2)$ for (3). The initial posture of the vehicle is $(-5, -7, \pi/4)$, and the desired posture is (0,0,0). The design parameters of the controller are chosen as: $k_1 = 3$, $k_2 = 3$, $k_3 = 0.3$; $K_c = 8I_3$, $\Gamma = I_9$, where I_k is a $k \times k$ identity matrix. The unmodelled disturbance is chosen as $\tau_d = [0.3 + 0.2\mathrm{sign}(u), 0.3 + 0.2\mathrm{sign}(v), 0.3 + 0.2\mathrm{sign}(r)]^\top$, and $k_d = [0.5, 0.5, 0.5]^\top$ is selected for the robust term (26).

The tracking control performance is depicted in Fig. 3. It is clearly seen that the ASV tracks the reference trajectory with high accuracy and has fast tracking speed, despite the existence of disturbance. Fig. 4 shows the tracking errors in X-and Y-directions and in orientation. It is shown that the tracking errors sharply converge to zero. The vehicle velocities and control forces are shown in Figs. 5 and 6, respectively. Note that no restrictions of magnitude are imposed in the simulation, but the required forces are still realistic and reasonable from a practical viewpoint.

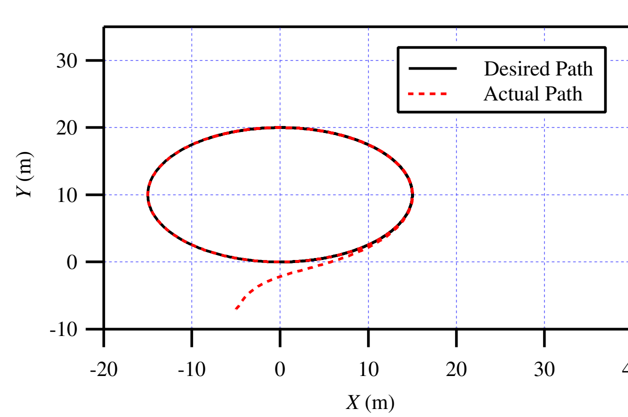


Fig. 3. Control performance of tracking an elliptic trajectory.

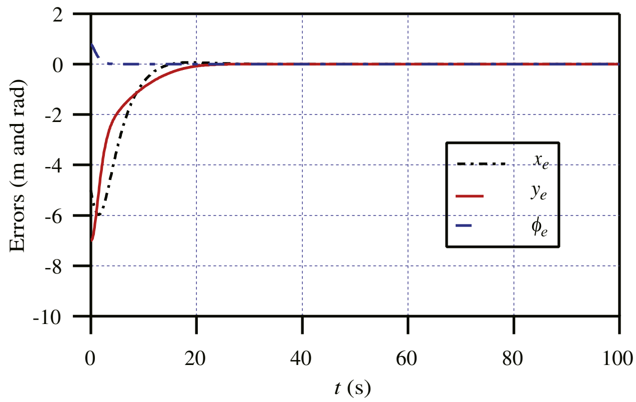


Fig. 4. Tracking errors in *X*- and *Y*-directions and in orientation.

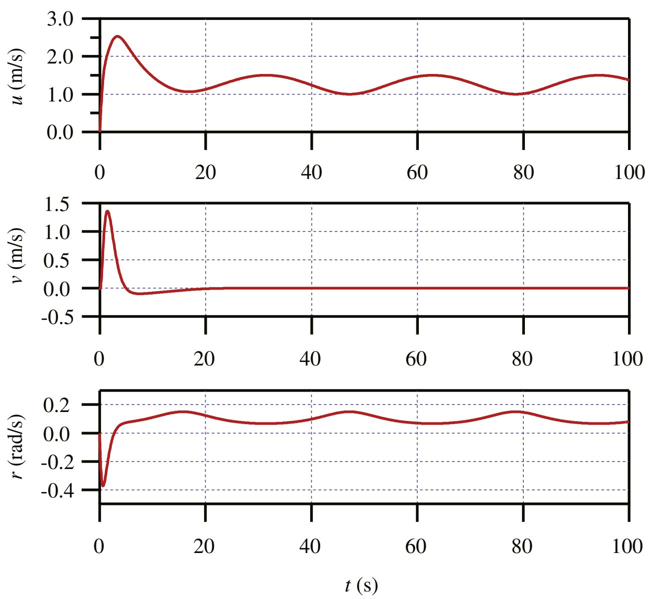


Fig. 5. Tracking velocities u, v and r.

4.2. Comparisons with other controllers

To show the efficiency of the proposed control approach, another special case of tacking a circular path is performed, and comparisons with a PID controller and a SMC controller are made.

The PID controller has the structure (Fossen, 2002):

$$\tau_{\text{pid}} = -K_P\eta_e(t) - K_D\dot{\eta}_e(t) - K_I\int_0^t \eta_e(\kappa)d\kappa, \tag{39}$$

with the PID gains $K_P = \text{diag}\{1,1,0.5\}$, $K_D = \text{diag}\{6,6,1\}$, and $K_I = \text{diag}\{0.05,0.04,0.05\}$. The SMC controller is defined as (Cheng et al., 2007):

$$\tau_{\text{smc}} = M\dot{v}_r + C(v)v_r + D(v)v_r + [C_\eta + D_\eta]s - M_\eta[Ls + K\text{sgn}(s)], \tag{40}$$

where $s = \dot{\eta}_e + \Lambda\eta_e$, $v_r = J^{-1}(\eta)(\dot{\eta}_d - \Lambda\eta_e)$, $M_\eta = MJ^{-1}(\eta)$, $C_\eta = [C(v) - MJ^{-1}(\eta)\dot{J}(\eta)]J^{-1}(\eta)$, $D_\eta = D(v)J^{-1}(\eta)$ with positive gains $L = \text{diag}\{1,5,5\}$, $K = \text{diag}\{0.1,0.1,0.1\}$, and $\Lambda = \text{diag}\{1,1,1\}$. The reference trajectory is given by

$$x_d = 10\sin(0.1t),$$
$$y_d = 10\cos(0.1t),$$

with constant desired velocities $u_d = 1$ m/s and $r_d = 0.1$ rad/s. The design parameters for the controller (21) are chosen as same with those of an ellipse. In addition, a more complicated time-dependent disturbance is considered as

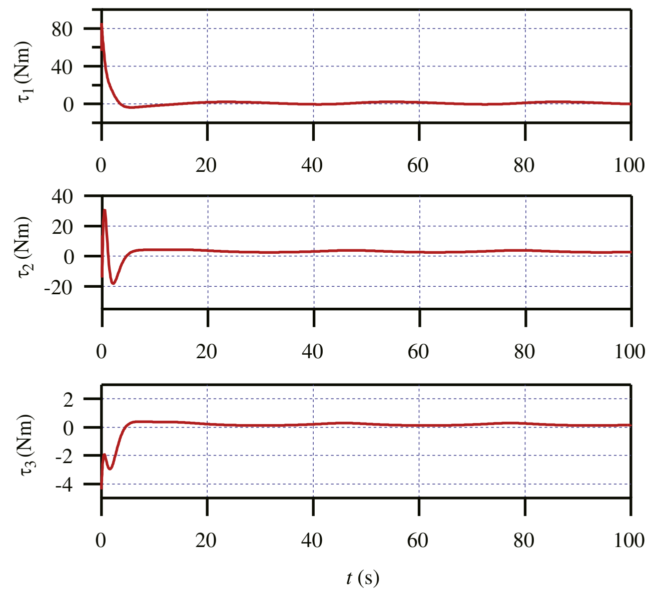


Fig. 6. Control forces τ_1, τ_2 and τ_3.

$$\tau_d = [1 + 0.1\sin(0.7t) + 0.3\sin(0.5t) + 0.5\cos(0.1t),$$
$$1 + 0.1\sin(0.7t) + 0.3\sin(0.5t) + 0.5\cos(0.1t),$$
$$1 + 0.1\sin(0.7t) + 0.3\sin(0.5t) + 0.5\cos(0.1t)]^\top$$

and $k_d = [1.95, 1.95, 1.95]^\top$ is selected for the robust term (26).

Fig. 7 shows the comparison of tracking performance among the proposed NN controller, SMC controller, and the PID controller. It is observed that the proposed NN controller tracks the reference path with the highest precision. To show the efficiency of the proposed controller better, define the error norm as

$$\|\eta_e\| = \sqrt{x_e^2 + y_e^2 + \phi_e^2}. \tag{41}$$

Fig. 8 shows the comparison results of tracking error norm $\|\eta_e\|$ among the three controllers. Notice that the PID controller has good steady-state performance, but less satisfactory transient performance, i.e., the tracking error suddenly has a peak at about 10 s. This is probably due to the linear control action that tends to produce large overshoots. Although the PID controller does not explicitly contain any terms from the ship model, the tuning of the PID gains is nontrivial, which usually requires advanced model-based techniques such as LQR. In addition, the proposed NN con-

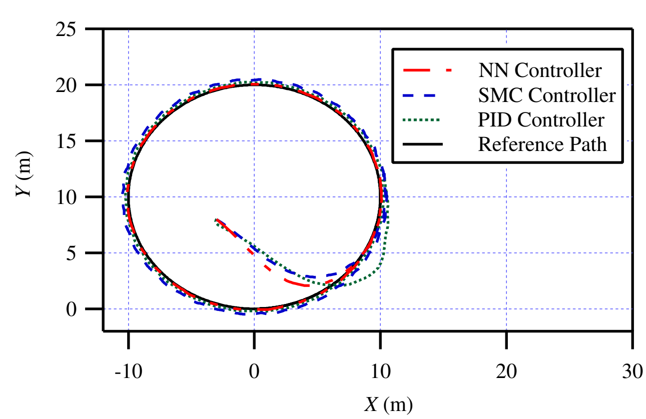


Fig. 7. Comparison of tracking performance.

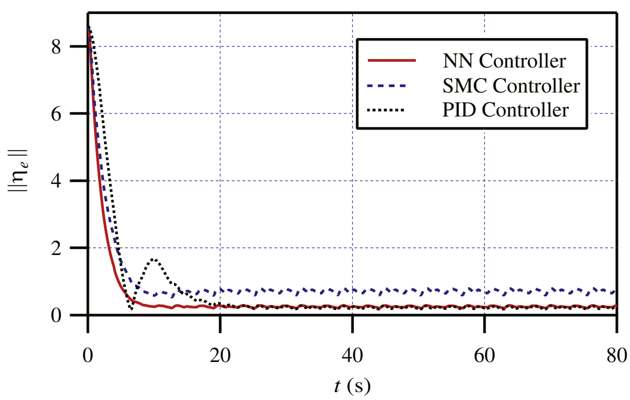


Fig. 8. Comparison of tracking error norm $\|\eta_e\|$.

troller performs better than the SMC controller with faster decay of tracking error and lower steady-state value. The better performance relies on the efficient learning of the single-layer NN and the compensation of the robust term. Note that no disturbance is considered in Cheng et al. (2007).

5. Conclusion

In this paper, an efficient NN approach is proposed for the real-time tracking control of an ASV with completely unknown vehicle dynamics, and subject to bounded unknown disturbance including unstructured, unmodelled dynamics. The proposed NN only has a single-layer structure by taking advantage of the vehicle regressor dynamics formulation. The learning algorithm derived from Lyapunov stability analysis is much simpler than other commonly used NN learning rules. It has shown that the proposed control algorithm is computationally efficient, and does not need any off-line training procedures. The stability of the control system is rigorously guaranteed by Lyapunov stability theorem. Simulation results demonstrate that the proposed controller is capable of driving the ASV to track the desired trajectory satisfactorily.

It is worth mentioning that although this paper does not take into account of the problem of input saturation, the forces generated are reasonable and feasible. In order to apply the proposed approach in practise more widely, it will be interesting to study the performance of the controller under the constraint of input saturation and actuator dynamics, which will be concerned in the future work.

Acknowledgements

This work was supported by the National Science Foundation of China under Grants 61074112 and 60674044, and Natural Sciences and Engineering Research Council (NSERC) Discovery Grant of Canada.

References

Aguiar, A. P., & Hespanha, J. P. (2007). Trajectory-tracking and path-following of underactuated autonomous vehicles with parametric modeling uncertainty. *IEEE Transactions on Automatic Control, 52*, 1362–1379.

Almeida, J., Silvestre, C., & Pascoal, A. (2007). Path-following control of fully-actuated surface vessels in the presence of ocean currents. In *Proceedings of 7th IFAC conference on control applications in marine systems*. Grand Hotel Elaphusa, Croatia.

Ashrafiuon, H., & McNinch, L. C. (2008). Sliding-mode tracking control of surface vessels. *IEEE Transactions on Industrial Electronics*, 55 4004–4012.

Benjamin, M. R., Curcio, J. A. (2004). Colregs-based navigation of autonomous marine vehicles. In *Proceedings of 2004 IEEE/OES autonomous underwater vehicles* (pp. 32–39). Sebasco Estates, USA.

Bibuli, M., Bruzzone, G., & Caccia, M. (2009). Path-following algorithms and experiments for an unmanned surface vehicle. *Journal of Field Robotics, 26*, 669–688.

Burns, R. S. (1995). The use of artificial neural networks for the intelligent optimal control of surface ships. *IEEE Journal of Oceanic Engineering, 20*, 65–72.

Caccia, M., Bibuli, M., Bono, R., Bruzzone, G., Bruzzone, G., & Spirandelli, E. (2007). Unmanned surface vehicle for coastal and protected water applications: The charlie project. *Marine Technology Society Journal, 41*, 62–71.

Caccia, M., Bruzzone, G., & Bono, R. (2008). A practical approach to modeling and identification of small autonomous surface craft. *IEEE Journal of Oceanic Engineering, 33*, 133–145.

Chen, C. H., Lin, C. M., & Chen, T. Y. (2008). Intelligent adaptive control for mimo uncertain nonlinear systems. *Expert Systems with Applications, 35*, 865–877.

Chen, M., Ge, S. S., & Choo, Y. S. (2009). Neural network tracking control of ocean surface vessels with input saturation. In *Proceedings of the IEEE international conference on automation and logistics* (pp. 85–89). Shenyang China.

Cheng, J., Yi, J., & Zhao, D. (2007). Design of a sliding mode controller for trajectory tracking problem of marine vessels. *IET Control Theory and Applications, 1*, 233–237.

Dai, S.L., Wang, C., & Luo, F. (in press). Identification and learning control of ocean surface ship using neural networks. *IEEE Transactions on Industrial Informatics*. DOI: http://dx.doi.org/10.1109/TII.2012.2205584.

Desa, E., Maurya, P. K., Pereira, A., Pascoal, A. M., Prabhudesai, R. G., Mascarenhas, A., et al. (2007). A small autonomous surface vehicle for ocean color remote sensing. *IEEE Journal of Oceanic Engineering, 32*, 353–364.

Du, J., & Guo, C. (2004). Nonlinear adaptive ship course tracking control based on backstepping and nussbaum gain. In *Proceedings of the 2004 American control conference* (pp. 3845–3850). Boston, USA.

Escario, J. B., Jimenez, J. F., & Giron-Sierra, J. M. (2012). Optimisation of autonomous ship manoeuvres applying ant colony optimisation metaheuristic. *Expert Systems with Applications, 39*, 10120–10139.

Fossen, T. I. (1994). *Guidance and control of ocean vehicles*. New York: Wiley.

Fossen, T. I. (2002). Marine control systems: Guidance, navigation and control of ships, rigs and underwater vehicles. *Marine Cybernetics*.

Fredriksen, E., & Pettersen, K. Y. (2006). Global kappa-exponential way-point maneuvering of ships: Theory and experiments. *Automatica, 42*, 677–687.

Iseki, T., & Ohtsu, K. (2000). Bayesian estimation of directional wave spectra based on ship motions. *Control Engineering Practice, 8*, 215–219.

Jiang, Z. (2002). Global tracking control of underactuated ships by lyapunovs direct method. *Automatica, 38*, 301–309.

Khalil, H. K. (1996). *Nonlinear Systems* (2nd ed.). Upper Saddle River: Prentice-Hall.

Liu, Z., Yu, R., & Zhu, Q. (2011). Stabilization control and simulation of an unmanned surface vessel. In *Proceedings of the 30th Chinese Control Conference* (pp. 3606–3609). Yantai, China.

Martins, A., Almeida, J.M., Silva, E.P., & Pereira, F.L. (2006). Vision-based autonomous surface vehicle docking manoeuvre. In *Proceedings of 7th IFAC conference on manoeuvring and control of marine craft*. Lisbon, Portugal.

Moreira, L., Fossen, C., & Guedes Soares, T. (2007). Path following control system for a tanker ship model. *Ocean Engineering, 34*, 2074–2085.

Park, J. S., Ohtsu, K., & Kitagawa, G. (2000). Batch-adaptive ship's autopilots. *International Journal of Adaptive Control and Signal Processing, 14*, 427–439.

Peng, J., & Dubay, R. (2012). Nonlinear inversion-based control with adaptive neural network compensation for uncertain mimo systems. *Expert Systems with Applications, 39*, 8162–8171.

Peng, Z., Wang, D., Chen, Z., Hu, X., & Lan, W. (in press). Adaptive dynamic surface control for formations of autonomous surface vehicles with uncertain dynamics. *IEEE Transactions on Control Systems Technology*. DOI: http://dx.doi.org/10.1109/TCST.2011.2181513.

Rigatos, G., & Tzafestas, S. (2006). Adaptive fuzzy control for the ship steering problem. *Mechatronics, 16*, 479–489.

Seo, K.-Y., Park, G.-K., Lee, C.-S., & Wang, M.-H. (2009). Ontology-based fuzzy support agent for ship steering control. *Expert Systems with Applications, 36*, 755–765.

Soyguder, S. (2011). Intelligent control based on wavelet decomposition and neural network for predicting of human trajectories with a novel vision-based robotic. *Expert Systems with Applications, 38*, 13994–14000.

Størkersen, N., Kristensen, J., Indreeide, A., Seim, J., & Glancy, T. (1998). Hugin-uuv for seabed surveying. *Sea Technology, 39*, 99–104.

Tee, K. P., & Ge, S. S. (2006). Control of fully actuated ocean surface vessels using a class of feedforward approximators. *IEEE Transactions on Control Systems Technology, 14*, 750–756.

Velagic, J., Vukic, Z., & Omerdic, E. (2003). Adaptive fuzzy ship autopilot for track-keeping. *Control Engineering Practice, 11*, 433–443.

Wu, J., Peng, H., Ohtsu, K., Kitagawa, G., & Itoh, T. (2012). Ship's tracking control based on nonlinear time series model. *Applied Ocean Research, 36*, 1–11.

Xu, T., Chudley, J., & Sutton, R. (2006). Soft computing design of a multi-sensor data fusion system for an unmanned surface vehicle navigation. In *Proceedings of 7th IFAC conference on manoeuvring and control of marine craft*. Lisbon, Portugal.

Yang, Y., Zhou, C., & Ren, J. (2003). Model reference adaptive robust fuzzy control for ship steering autopilot with uncertain nonlinear systems. *Applied Soft Computing, 3*, 305–316.

Zhang, L.-J., Jia, H.-M., & Qi, X. (2011). NNFFC-adaptive output feedback trajectory tracking control for a surface ship at high speed. *Ocean Engineering, 38*, 1430–1438.

Zhang, Y., Hearn, G. E., & Sen, P. (1996). A neural network approach to ship track-keeping control. *IEEE Journal of Oceanic Engineering, 21*, 513–527.

Zou, J., Chen, M., Feng, X., & Liu, M. (2011). Robust tracking control of ocean surface vessels using disturbance observer. In *Proceedings of the 30th chinese control conference*. (pp. 6176–6180). Yantai, China.