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*T*racking Control of a Marine Surface Vessel with Full-State Constraints

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In this paper, a trajectory tracking control law is proposed for a class of marine surface vessels in the presence of full-state constraints and dynamics uncertainties. A barrier Lyapunov function (BLF) based control is employed to prevent states from violating the constraints. Neural networks are used to approximate the system uncertainties in the control design, and the control law is designed by using the Moore-Penrose inverse. The proposed control is able to compensate for the effects of full-state constraints. Meanwhile, the signals in the closed loop system are guaranteed to be semiglobally uniformly bounded (SGUB), with the asymptotic tracking being achieved. Finally, the performance of the proposed control has been tested and verified by simulation studies.

Keywords: Learning Control; State Constraints; Marine Surface Vessel; Barrier Lyapunov Function; Adaptive Control; Neural Networks.

1. Introduction

In recent years, the marine surface vessel has been broadly applied in ocean engineering. There have been numerous research in the control design for marine surface vessels Chen *et al.* (2013); Cui *et al.* (2010); He *et al.* (2011, 2016, In Press, DOI: 10.1109/TCYB.2016.2554621); Wang *et al.* (2016, In Press, DOI: 10.1109/TCYB.2015.2451116); Yin *et al.* (2015). Therefore, in order to enable the marine vessel to track the desired trajectory accurately, extensive research work has been carried out to investigate the control problem Wang and Er (2016, In Press, DOI: 10.1109/TCST.2015.2510587); Yin *et al.* (2014).

Ensuring stability is a challenging problem for nonlinear control design of marine vessels in the harsh oceanic environment. In addition, the vessel dynamics contain unknown parameters and is also affected by external disturbances. Thus, it is necessary to design robust controllers for marine surface vessels. Neglecting this problem may lead to performance degradation or even destabilization. On the other hand, state constraint is also a problem that needs to be solved in the tracking of a marine surface vessel. In practice, constraints on system inputs and states are ubiquitous and always manifest themselves when there are specific requirement of performance

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and specifications of safety He *et al.* (2016*a*,*b*); Hou *et al.* (2010); Hu and Lin (2001); Li *et al.* (In Press, 2016, In Press, DOI: 10.1109/TIE.2016.2538741); Liu and Tong (2015*b*); Zhou *et al.* (DOI: 10.1109/TSMC.2016.2557222, 2016, 2015). Violation of the state constraint may cause hazards, system damage or environment pollution. For example, a marine vessel needs to avoid running against the rock when it sails in the see. And a vessel's running speed should not go beyond the appropriate speed limit set in the navigation manual, to avoid engine damage and even accidents. Designing a controller without taking into account these constraints can lead to failure of control. Therefore, it is important to take into consideration of these problems in the control design.

To solve the problem associated with system uncertainties, numerous control approaches have been proposed for marine surface vessels. For example, in Ashrafiuon *et al.* (2008); Rong *et al.* (2012), sliding-mode based control laws are developed. A first-order sliding surface in terms of surge tracking errors and a second-order surface in terms of lateral motion tracking errors are introduced by Ashrafiuon in the control design. In Tee and Ge (2006), the authors considered the problem of tracking a desired trajectory for fully actuated ocean vessels, in the presence of uncertainties and unknown disturbances. In Du *et al.* (2010), the author designed a ship trajectory tracking control law based on the nonlinear ship surface movement mathematical model including the Coriolis and centripetal matrix and nonlinear damp terms. In Ghommam *et al.* (2006), the authors employed the backstepping technique, to design a discontinuous feedback controller for underactuated surface vessels. In Dai *et al.* (2012), the authors presented the problems of accurate identification and learning control of ocean surface vessel with uncertain dynamical environments. In this paper, we consider employ neural networks to approximate the uncertainties in the vessel dynamics.

In Yang *et al.* (2014), the optimized adaptive control for a class of wheeled inverted pendulum (WIP) systems was investigated, employing neural networks to handle the internal and external uncertainties. In practice, we also need to consider position and velocity constraints which is not practical in the actual life. In the distributed system, the constraint is also widespread He and Zhang (2016, In Press, DOI: 10.1109/TCST.2016.2536708); He and Ge (2015, 2016). To avoid the violation of constraints, many methods for dealing with constrained nonlinear systems have been proposed such as constrained model predictive control Mayne *et al.* (2000), reference governor Alberto (1998), command governor Gilbert and Chong-Jin (2009), adaptive control He *et al.* (2014); Hu and Zheng (2014); Liu and Tong (2016); Wang *et al.* (2016, In Press, DOI: 10.1109/TCST.2015.2496585), fuzzy control Xie *et al.* (2014, 2016), fault-tolerant control Peng *et al.* (2016, 2015) extremum seeking control DeHaan and Guay (2005), robust control Guo *et al.* (2015*a*,*b*) and neural network control Cheng *et al.* (2010); He *et al.* (2016, In Press, DOI: 10.1109/TSMC.2015.2466194); Liu *et al.* (2015*a*); Sun *et al.* (2016, In Press, DOI: 10.1109/TSMC.2016.2557223); Yang *et al.* (2013). Among them, the barrier Lyapunov function (BLF) is a kind of control Lyapunov functions which have been developed to guarantee the constraints are not violation Ren *et al.* (2010); Tee *et al.* (2009). Inspired by the BLF's property, BLF based methods have been used in constrained nonlinear systems in Brunovsky form Ngo *et al.* (2005) and output feedback form Ren *et al.* (2010). In Li *et al.* (2012), the authors propose robust adaptive control strategies for Remotely Operated Vehicles (ROVs) with velocity constraints in the presence of uncertainties and disturbances. Nonetheless, all of the aforementioned achievements using BLFs require the system dynamics to be at least partially known. In this paper, the tracking control of state constrained vessel systems with unknown system dynamics is investigated, which are approximated by the neural networks.

Recently, the NN control of the nonlinear systems with uncertainties and constraints has been proposed in Chen *et al.* (2011); Dai *et al.* (2014); Li *et al.* (DOI: 10.1109/TAC.2015.2503566, 2016, 2014); Liu *et al.* (2014*a*,*b*); Liu and Tong (2015*a*); Liu *et al.* (2015*b*); Sun and Xia (2009); Xu *et al.* (2014); Yang *et al.* (2015). A framework for synchronised tracking control of a general class of high-order single-input-single-output (SISO) systems with unknown dynamics is also proposed in Cui *et al.* (2012). In Li and Su (2013), adaptive neural network control is investigated for single-master-multiple-slaves teleoperation considering time delays and input dead zone nonlinearities for multiple mobile manipulators carrying a common object in a cooperative manner. A neural network controller for a general serial-link robot arm is developed in Lewis *et al.* (1995), and a multilayer neural network-based controller for a class of single-input single-output continuous-time nonlinear system is designed in Yeşildirek and Lewis (1995). A barrier Lyapunov function increases to infinity whenever its arguments closes to some specified values. Therefore, keeping the BLF bounded could ensure that the constraints are never violated in the closed-loop system. In Tee *et al.* (2011), the authors address the problem of control design for a class of strict-feedback systems with constraints on the partial states. In addition, the authors present control of state constrained nonlinear systems in strict feedback form to achieve output tracking Tee and Ge (2009). In Huusom *et al.* (2010), the authors present a state feedback control system with a state observer. In Tee *et al.* (2011), the authors address the problem of control design for strict-feedback systems with constraints on the partial states. In this paper, we extend the aforementioned work to a more challenging problem wherein constraints in all the states and the system dynamics are a three degree-of-freedom marine surface vessel with multiple-input-multiple-output. The greatest challenge of this problem comes from that the system is a multiple-input-multiple-output, such that all the states and controller need to use the vector. Therefore, in this paper the Moore-Penrose inverse term is applied to design the controller.

The rest of this paper is organized as follows. Section 2 covers the preliminaries and the dynamics of a 3 degree-of-freedom marine surface vessel with multiple-input-multiple-output. In Section 3, we design an adaptive neural networks control by employing a BLF and neural networks. In Section 4, simulation studies are carried out to illustrate the feasibility of the proposed control. The last section concludes the work in our paper.

2. Problem Formulation

2.1. *Problem Formulation*

The motions and state variables of the single point mooring systems are defined and measured with respect to two important reference frames: earth-fixed frame, body-fixed frame. Fig. 1 shows the earth-fixed frame is denoted as (x_e, y_e) with its origin located at the connection of the mooring line and the mooring terminal. The body-fixed frame, denoted as (x_b, y_b), is fixed to the vessel body, that is, the origin coincides with the center of gravity of the moored vessel. The x_b axis is directed from poop to fore along the longitudinal axis of the vessel and the y_b axis is directed to starboard.

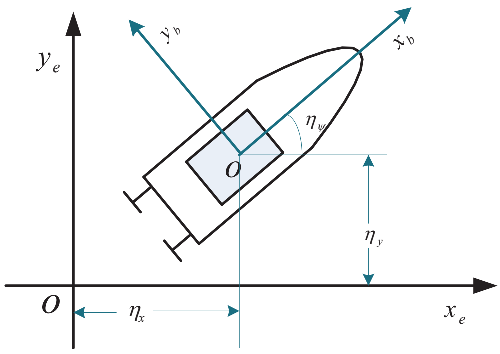

Figure 1. The diagram of the marine surface vessel system

The dynamics of a 3 degree-of-freedom (DOF) marine surface vessel with multiple-input-multiple-output (MIMO) Tee and Ge (2006) are described as follow

$$\begin{aligned} \dot{\eta} &= J(\eta)\upsilon \\ M\dot{\upsilon} + C(\upsilon)\upsilon + D(\upsilon)\upsilon + g(\eta) &= \tau \end{aligned} \tag{1}$$

where the output $\eta = [\eta_x, \eta_y, \eta_\psi] \in \mathbb{R}^3$ represents the Earth-frame positions and heading, respectively, $\tau \in \mathbb{R}^3$ is the control input, $\upsilon = [\upsilon_x, \upsilon_y, \upsilon_\psi] \in \mathbb{R}^3$ denotes the velocities of vessel in the vessel-frame system. $M \in \mathbb{R}^{3\times3}$ is a symmetric positive definite inertia matrix, $C(\upsilon) \in \mathbb{R}^{3\times3}$ is the Centripetal and Coriolis torques, and $D(\upsilon) \in \mathbb{R}^{3\times3}$ is the damping matrix, $g(\eta)$ represents the restoring forces caused by force of gravity, ocean currents and floatage, $J(\eta)$ is the transformation matrix which is assumed to be nonsingular, and it is defined as

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

Let $x_1 = \eta, x_2 = \upsilon$, then the vessel system can be described as

$$\begin{aligned} \dot{x}_1 &= J(x_1)x_2 \\ \dot{x}_2 &= M^{-1}[\tau - C(x_2)x_2 - D(x_2)x_2 - g(x_1)] = a \end{aligned} \tag{2}$$

The control objective is to track a desired trajectory of the earth-frame positions $x_d(t) = [x_{d1}(t), x_{d2}(t), x_{d3}(t)]^T$, and desired trajectory of the velocities $x_{2d} = [x_{2d1}(t), x_{2d2}(t), x_{2d3}(t)]^T$. While ensuring that all signals are bounded and that the full-state constraints are not violated, i.e., $|x_1| \le k_{c1}, |x_2| \le k_{c2}, \forall t \ge 0$, where $k_{c1} = [k_{c11}, k_{c12}, k_{c13}]^T$, $k_{c2} = [k_{c21}, k_{c22}, k_{c23}]^T$ are positive constant vectors.

Assumption 1: For any $k_{c1} > 0$, there exist positive vectors $\mathbf{Y}_0 = [Y_{01}, Y_{02}, Y_{03}]^T, \mathbf{Y}_1 = [Y_{11}, Y_{12}, Y_{13}]^T, \mathbf{A_0} = [A_{01}, A_{02}, A_{03}]^T$, satisfying $\mathbf{Y}_0 \le \mathbf{A_0} \le k_{c1}$, such that, $\forall t \ge 0$, the desired trajectory $x_d(t)$ and its time derivatives satisfy $-\mathbf{Y}_0 \le x_d(t) \le \mathbf{Y}_0$, $|\dot{x}_d(t)| \le \mathbf{Y}_1$.

Assumption 1 implies that the desired trajectory $x_d(t)(\forall t \ge 0)$ and its first order derivatives are continuous, and bounded.

3. Control Design

3.1. *Model Based Control*

In case that the parameters M, $C(\upsilon)$, $D(\upsilon)$ and $g(\eta)$ are known, we denote $z_1 = [z_{11}, z_{12}, z_{13}]^T = x_1 - x_d$, and $z_2 = [z_{21}, z_{22}, z_{23}]^T = x_2 - \alpha$. Choosing the asymmetric barrier Lyapunov function as

$$V_1 = \frac{1}{2}\sum_{i=1}^{3} \log \frac{k_{ai}^2}{k_{ai}^2 - z_{1i}^2} \tag{3}$$

where $k_a = k_{c1} - \mathbf{X_0} = [k_{a1}, k_{a2}, k_{a3}]^T$, then differentiating of V_1 with respect to time we have

$$\dot{V}_1 = \sum_{i=1}^{3} \frac{z_{1i}\dot{z}_{1i}}{k_{ai}^2 - z_{1i}^2} \tag{4}$$

Differentiating of z_1 with respect to time, we have

$$\dot{z}_1 = \dot{x}_1 - \dot{x}_d = J(x_1)x_2 - \dot{x}_d = J(x_1)(z_2 + \alpha) - \dot{x}_d \tag{5}$$

$$\dot{z}_{1i} = J_i(x_1)(z_2 + \alpha) - \dot{x}_{di} \tag{6}$$

where $J_i(x_1)$ is the ith line of $J(x_1)$. We propose α as

$$\alpha = J^T(\dot{x}_d - A_1) \tag{7}$$

where

$$A_1 = \begin{bmatrix} (k_{a1}^2 - z_{11}^2)k_{11}z_{11} \\ (k_{a2}^2 - z_{12}^2)k_{12}z_{12} \\ (k_{a3}^2 - z_{13}^2)k_{13}z_{13} \end{bmatrix} \tag{8}$$

$k_{1i},\ i = 1, 2, 3$ are positive constants.

Assumption 2: The matrix $J(x_1)$ is known, and there exists a boundary. From assumption 1, we can further assume that there exist positive vectors $\mathbf{B_0} = [B_{01}, B_{02}, B_{03}]^T$ and $\mathbf{X_0} = [X_{01}, X_{02}, X_{03}]^T$, satisfying $\mathbf{X_0} \leq \mathbf{B_0} \leq k_{c2}$, such that, $\forall t \geq 0$, $\alpha(t)$ satisfies $-\mathbf{X}_0 \leq \alpha(t) \leq \mathbf{X}_0$.

Assumption 2 implies that α is continuous, and bounded.
Substituting (6), (7) and (8) into (4) we can obtain

$$\dot{V}_1 = -\sum_{i=1}^{3} k_{1i}z_{1i}^2 + \sum_{i=1}^{3} \frac{z_{1i}J_i z_2}{k_{ai}^2 - z_{1i}^2} \tag{9}$$

Then we consider a barrier Lyapunov function candidate as

$$V_2 = V_1 + \frac{1}{2}\sum_{i=1}^{3} \log \frac{k_{bi}^2}{k_{bi}^2 - z_{2i}^2} + \frac{1}{2} z_2^T M z_2 \tag{10}$$

where $k_b = k_{c2} - \mathbf{Y_0} = [k_{b1}, k_{b2}, k_{b3}]^T$, then differentiating (10) with respect to time leads to

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + \sum_{i=1}^{3} \frac{z_{2i}\dot{z}_{2i}}{k_{bi}^2 - z_{2i}^2} + z_2^T M \dot{z}_2 \\ &= -\sum_{i=1}^{3} k_{1i}z_{1i}^2 + \sum_{i=1}^{3}\left(\frac{z_{1i}J_i z_2}{k_{ai}^2 - z_{1i}^2} + \frac{z_{2i}\dot{z}_{2i}}{k_{bi}^2 - z_{2i}^2}\right) + z_2^T M \dot{z}_2 \end{aligned} \tag{11}$$

Differentiating z_2 with respect to time, we have

$$\dot{z}_2 = M^{-1}[\tau - C(x_2)x_2 - D(x_2)x_2 - g(x_1)] - \dot{\alpha} \tag{12}$$

According to the Moore-Penrose inverse, we can obtain

$$z_2^T(z_2^T)^+ = \begin{cases} 0, & z_2 = [0, 0, 0]^T \\ 1, & \text{Otherwise} \end{cases} \tag{13}$$

When $z_2 = [0,0,0]^T$, $\dot{V}_2 = -\sum_{i=1}^{3} k_{1i} z_{1i}^2 \leq 0$. Then asymptotic stability of the system can still be drawn by the Barbalat's lemma Slotine and Weiping (1991). Otherwise in case of $z_2 \neq [0,0,0]^T$, we designed the model-based control as

$$\tau = C(x_2)x_2 + D(x_2)x_2 + g(x_1) + M\dot{\alpha} - \sum_{i=1}^{3} \frac{z_{1i} J_i^T}{k_{ai}^2 - z_{1i}^2} - (z_2^T)^+ \sum_{i=1}^{3} \frac{z_{2i}(a_i - \dot{\alpha}_i)}{k_{bi}^2 - z_{2i}^2} - K_2 z_2 \tag{14}$$

where K_2 is a control gain. Then substituting (12) and (14) into (11), we can get

$$\dot{V}_2 = -\sum_{i=1}^{3} k_{1i} z_{1i}^2 - z_2^T K_2 z_2 < 0 \tag{15}$$

According to Lemma 1, we know the signal z_1 remains in the interval $-k_a \leq z_1 \leq k_a, \forall t > 0$, similarly, the signal z_2 remains in the interval $-k_b \leq z_2 \leq k_b, \forall t > 0$.

3.2. *Adaptive Neural Network Control with Full-State Feedback*

The parameters of the marine vessel system $M, C(x_2), D(x_2), g(x_1)$ may be unknown in practise, and in this case the control law above can be implementable. To handle this problem we use a approximator based on neural networks to approximate the unknown parameters. In the following we will design an adaptive neural network control.
The adaptive law is proposed as follows

$$\dot{\hat{W}}_i = \Gamma_i[S_i(Z_i)z_{2,i} - \sigma_i|z_{2i}|\hat{W}_i], i = 1,2,3 \tag{16}$$

where $\hat{W} = [\hat{W}_1, \hat{W}_2, \hat{W}_3]^T$ are the weights of the neural networks, $S(Z) = [S(Z)_1, S(Z)_2, S(Z)_3]$ is the basis functions, and $Z = [x_1^T, x_2^T, \alpha^T, \dot{\alpha}^T]$ are the inputs of the neural networks, and $\Gamma_i = \Gamma_i^T > 0$ $(i = 1,2,3)$ is the constant gain matrix, $\sigma_i > 0, i = 1,2,3$ are small constants.

Lemma 3.1: *Meng* et al. *(2012) For adaptive law (16), there exits a compact set*

$$\Omega_{\omega 1} = \left\{ \hat{W}_i \middle| \|\hat{W}_i\| \leq \frac{s_i}{\sigma_i} \right\}$$

where $\|S_i(Z)\| \leq s_i$ *with* $\phi_i > 0$*, such that* $\hat{W}_i(t) \in \Omega_{\omega 1}$*,* $\forall t \geq 0$ *provided that* $\hat{W}_i(0) \in \Omega_{\omega 1}$*.*

Proof: Let $V_{\omega 1} = \frac{1}{2}\hat{W}_i^T \Gamma_i^{-1} \hat{W}_i$, its time derivative is

$$\begin{aligned} \dot{V}_{\omega 1} &= \hat{W}_i^T (S_i(Z)z_{2,i} - \sigma_i|z_{2i}|\hat{W}_i) \\ &\leq -|z_{2i}|\|\hat{W}_i\|(\sigma_i\|\hat{W}_i\| - s_i) \end{aligned}$$

$\dot{V}_{\omega 1}$ will become negative as long as $\|\hat{W}_i\| > \frac{s_i}{\sigma_i}$. Therefore, $\hat{W}_i \in \Omega_{\omega 1}$ if $\hat{W}_i(0) \in \Omega_{\omega 1}$ for $t \geq 0$. ■

The neural network $\hat{W}^T S(Z)$ is used to approximate $W^{*T} S(Z)$.

$$W^{*T} S(Z) = \hat{W}^T S(Z) - \epsilon(Z) = -(C(x_2)x_2 + D(x_2)x_2 + g(x_1) + M\dot{\alpha}) - \epsilon(Z) \tag{17}$$

where $\tilde{W}_i = \hat{W}_i - W_i^*$ and $\tilde{W}_i$, $\hat{W}_i$, W_i^* are the NN weight errors, estimate and actual value respectively.

Then, we propose the following control as

$$\tau = -(z_2^T)^+ \sum_{i=1}^{3} [\frac{z_{2i}(a_i - \dot{\alpha}_i)}{k_{bi}^2 - z_{2i}^2} + \frac{k_{1i}z_{1i}^2}{k_{ai}^2 - z_{1i}^2} + \frac{k_{2i}z_{2i}^2}{k_{bi}^2 - z_{2i}^2}] - \sum_{i=1}^{3} \frac{z_{1i}(J_i)^T}{k_{ai}^2 - z_{1i}^2} - \hat{W}^T S(Z) - K_3 z_2 \tag{18}$$

where K_3 is the control gain. In the following part, we are ready to present the stability theorem of the closed-loop system.

Theorem 3.2: *Consider the marine surface vessel dynamics (1), under Assumption 1, with the state feedback control law (18) together with adaption law (16), for initial conditions satisfy* $z_1(0) \in \Omega_0 := \{z_1 \in \mathbb{R}^3 : -k_a < z_1 < k_a\}$, *and* $z_2(0) \in \Omega_0 := \{z_2 \in \mathbb{R}^3 : -k_b < z_2 < k_b\}$, *i.e., the initial conditions are bounded. The signals of the closed loop system are semiglobally uniformly bounded (SGUB). And the asymptotic tracking is achieved, i.e.,* $x_1(t) \to x_d(t)$, *and* $x_2(t) \to \alpha(t)$ *as* $t \to \infty$. *The multiple full-state constraints are never violated, i.e.,* $|x_1| < k_{c1}$, $|x_2| < k_{c2}, \forall t > 0$, *and the closed-loop error signals* z_1 *and* z_2 *will remain within the compact sets* Ω_{z1}, Ω_{z2}, *respectively, defined by*

$$\Omega_{z1} := \{z_1 \in \mathbb{R}^3 | \, \|z_{1i}\| \le \sqrt{k_{ai}^2(1 - e^{-D})}, i = 1,2,3\} \tag{19}$$

$$\Omega_{z2} := \{z_2 \in \mathbb{R}^3 | \, \|z_{2i}\| \le \sqrt{\frac{D}{\lambda_{\min}(M)}}, i = 1,2,3\} \bigcap \{z_{2i} \in \mathbb{R}^3 | \, \|z_2\| \le \sqrt{k_{bi}^2(1 - e^{-D})}, i = 1,2,3\} \tag{20}$$

where $D = 2(V_3(0) + C/\rho)$, ρ *and* C *are two positive constants.*

Proof: Consider the following Lyapunov candidate function

$$V_3 = V_2 + \frac{1}{2}\sum_{i=1}^{3} \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \tag{21}$$

Taking $\dot{z}_2 = \dot{x}_2 - \dot{\alpha} = a - \dot{\alpha}$ and differentiating V_3 with respect to time, we have

$$\begin{aligned}\dot{V}_3 = &- \sum_{i=1}^{3} k_{1i} z_{1i}^2 + \sum_{i=1}^{3} \frac{z_{1i} J_i z_2}{k_{ai}^2 - z_{1i}^2} + \sum_{i=1}^{3} \frac{z_{1i}(a_i - \dot{\alpha}_i)}{k_{bi}^2 - z_{2i}^2} + \sum_{i=1}^{3} \tilde{W}_i^T \Gamma_i^{-1} \dot{\tilde{W}}_i \\ &+ z_2^T [\tau - C(x_2)x_2 - D(x_2)x_2 - g(x_1) - M\dot{\alpha}]\end{aligned} \tag{22}$$

Substituting (16), (17) and (18) into (22), we can obtain

$$\begin{aligned}\dot{V}_3 = &- \sum_{i=1}^{3} k_{1i} z_{1i}^2 + \sum_{i=1}^{3} \frac{z_{2i}(a_i - \dot{\alpha}_i) - z_2^T (z_2^T)^+ z_{2i}(a_i - \dot{\alpha}_i)}{k_{bi}^2 - z_{2i}^2} + \sum_{i=1}^{3} \tilde{W}_i^T S_i(Z) z_{2,i} - \sum_{i=1}^{3} \tilde{W}_i^T |z_{2i}| \hat{W}_i \\ &+ z_2^T (W^{*T} S(Z) - \hat{W}^T S(Z) + \epsilon(Z)) - z_2^T K_3 z_2 - \sum_{i=1}^{3} \frac{z_2^T (z_2^T)^+ k_{1i} z_{1i}^2}{k_{ai}^2 - z_{1i}^2} - \sum_{i=1}^{3} \frac{z_2^T (z_2^T)^+ k_{2i} z_{2i}^2}{k_{bi}^2 - z_{2i}^2}\end{aligned} \tag{23}$$

When $z_2 = [0,0,0]^T$, $\dot{V}_2 = -\sum_{i=1}^{3} k_{1i} z_{1i}^2$, according to the Barbalat's lemma, we can still be drawn a conclusion on the asymptotic stability of the system. Otherwise, in case of $z_2 \neq [0,0,0]^T$, we have

$$\dot{V}_3 \leq -z_2^T (K_3 - I) z_2 - \sum_{i=1}^{3} \frac{k_{1i} z_{1i}^2}{k_{ai}^2 - z_{1i}^2} - \sum_{i=1}^{3} \frac{k_{2i} z_{2i}^2}{k_{bi}^2 - z_{2i}^2} + \sum_{i=1}^{3} \frac{\sigma_i^2}{8} (\|W_i^*\|^4 + \|\tilde{W}_i\|^4 - 2\|W_i^*\|^2 \|\tilde{W}_i\|^2) + \frac{1}{2} \|\bar{\epsilon}(Z)\|^2 \tag{24}$$

From lemma 3.1, we can obtain

$$\|\tilde{W}_i\| = \|\hat{W}_i - W_i^*\| \leq \frac{s_i}{\sigma_i} + \|W_i^*\| = \vartheta_i \tag{25}$$

Therefore, we have

$$\dot{V}_3 \leq -\rho V_3 + C \tag{26}$$

where

$$\rho = \min \left(\min(2k_{1i}), \min(2k_{2i}), \frac{2\lambda_{\min}(K_3 - I)}{\lambda_{\max}(M)}, \min \left(\frac{\sigma_i^2 \|W_i^*\|^2}{2\lambda_{\max}(\Gamma_i^{-1})} \right) \right) \tag{27}$$

$$C = \frac{1}{2} \|\bar{\epsilon}(Z)\|^2 + \sum_{i=1}^{3} \frac{\sigma_i^2}{8} (\|W_i^*\|^4 + \vartheta_i^4) \tag{28}$$

where $\lambda_{\min}(\bullet)$ and $\lambda_{\max}(\bullet)$ denote the minimum and maximum eigenvalues of matrix $\bullet$, where $\lambda(A)$ are real, respectively. To ensure $\rho > 0$, the control gain K_3 is chosen to satisfy the following condition:

$$\lambda_{\min}(K_3 - I) > 0 \tag{29}$$

According to Lemma 1, $z_1(t)$ remains in the open set $z_1 \in (-k_a, k_a), \forall t \in [0, +\infty)$, provided that $z_1(0) \in (-k_a, k_a)$. As we know $x_1(t) = z_1(t) + x_d(t)$, $-\mathbf{X}_0 \leq x_d(t) \leq \mathbf{X}_0$, $k_a = k_{c1} - \mathbf{X}_0$, and we known $z_2(t)$ remains in the open set $z_2 \in (-k_b, k_b), \forall t \in [0, +\infty)$, provided that $z_2(0) \in (-k_b, k_b)$, and $x_2(t) = z_2(t) + \alpha(t)$, $-\mathbf{Y}_0 \leq \alpha(t) \leq \mathbf{Y}_0$, $k_b = k_{c2} - \mathbf{Y}_0$ similarly. Hence, the constraints are not violated, i.e., $|x_1| \leq k_{c1},\ |x_2| \leq k_{c2}, \forall t \geq 0$. Multiplying (26) by $e^{\rho t}$, we can obtain

$$\frac{d}{dt}(V_3 e^{\rho t}) \leq C e^{\rho t} \tag{30}$$

Integrating the above inequality, we obtain

$$V_3 \leq V_3(0) + \frac{C}{\rho} \tag{31}$$

According to (21), we have

$$\frac{1}{2}\|z_2\|^2 \leq \frac{V_3(0) + \frac{C}{\rho}}{\lambda_{\min}(M)} \tag{32}$$

and, we have

$$\frac{1}{2}\log\frac{k_{bi}^2}{k_{bi}^2 z_{2i}^2} \leq V_3(0) + \frac{C}{\rho}$$

$$\|z_{2i}\| \leq \sqrt{k_{bi}^2(1 - e^{2(V_3(0)+\frac{C}{\rho})})} \tag{33}$$

For z_1, we obtain

$$\frac{1}{2}\log\frac{k_{ai}^2}{k_{ai}^2 z_{1i}^2} \leq V_3(0) + \frac{C}{\rho}$$

$$\|z_{1i}\| \leq \sqrt{k_{ai}^2(1 - e^{2(V_3(0)+\frac{C}{\rho})})} \tag{34}$$

■

Therefore, we can conclude that the signals z_1 and z_2 are semiglobally uniformly bounded.

4. Simulation

Consider the vessel with model of Cybership II, which is a 1:70 scale supply vessel replica built in a marine control laboratory in the Norwegian University of Science and Technology Skjetne *et al.* (2005). We choose the desired trajectories as follows:

$$x_{1d}(t) = [x_{1xd}(t), x_{1yd}(t), x_{1\psi d}(t)] \tag{35}$$

$$\begin{cases} x_{1xd}(t) = 40\sin 0.5t \\ x_{1yd}(t) = 14\cos 2t \\ x_{1\psi d}(t) = \tan^{-1}(\frac{\dot{x_{1yd}}}{\dot{x_{1xd}}}) \end{cases} \tag{36}$$

$$J^{-1}x_{1d} = x_{2d} \tag{37}$$

The symmetric positive definite inertia matrix M, the Centripetal and Coriolis torques $C(\upsilon)$, and the damping matrix $D(\upsilon)$ are given as

$$M = \begin{bmatrix} m - X_{du} & 0 & 0 \\ 0 & m - Y_{dv} & mx_g - Y_{dr} \\ 0 & mx_g - Y_{dr} & I_z - N_{dr} \end{bmatrix}$$

$$C(\upsilon) = \begin{bmatrix} 0 & 0 & (-m - Y_{dv})\upsilon_y - (mx_g - Y_{dr})\upsilon_\psi \\ 0 & 0 & (m - X_{du})\upsilon_x \\ (m - Y_{dv})\upsilon_y + (mx_g - Y_{dr})\upsilon_\psi & (m - X_{du})\upsilon_x & 0 \end{bmatrix}$$

$$D(\upsilon) = \begin{bmatrix} -X_u - X_{uu}|\upsilon_x| - X_{uuu}\upsilon_x^2 & 0 & 0 \\ 0 & -Y_v - Y_{vv}|\upsilon_y| - Y_{rv}|\upsilon_\psi| & -Y_r - Y_{vr}|\upsilon_y| - Y_{rr}|\upsilon_\psi| \\ 0 & -N_v - N_{vv}|\upsilon_y| - N_{rv}|\upsilon_\psi| & -N_r - N_{vr}|\upsilon_y| - N_{rr}|\upsilon_\psi| \end{bmatrix}$$

where

$D_{11} = -X_u - X_{uu}|\upsilon_x| - X_{uuu}\upsilon_x^2, D_{22} = -Y_v - Y_{vv}|\upsilon_y| - Y_{rv}|\upsilon_\psi|, D_{23} = -Y_r - Y_{vr}|\upsilon_y| - Y_{rr}|\upsilon_\psi|,$
$D_{32} = -N_v - N_{vv}|\upsilon_y| - N_{rv}|\upsilon_\psi|, D_{33} = -N_r - N_{vr}|\upsilon_y| - N_{rr}|\upsilon_\psi|$

In this paper, the parameters are chosen as $m = 23.8$, $I_z = 1.76$, $x_g = 0.046$, $X_u = -0.7225$, $X_{uu} = -1.3274$, $X_{uuu} = -5.8664$, $Y_v = -0.8612$, $Y_{vv} = -36.2823$, $Y_r = 0.1079$, $N_v = 0.1052$, $N_{vv} = 5.0437$, $X_du = -2.0$, $Y_{dv} = -10.0$, $Y_{dr} = -0$, $N_{dv} = 0$, $N_{dr} = -1.0$, $Y_{rv} = 2$, $Y_{vr} = 1$, $Y_{rr} = 3$, $N_{rv} = 5$, $N_r = 4$, $N_{vr} = 0.5$, $N_{rr} = 0.8$.

We have proposed three cases for the simulation studies. Firstly, we give the mode-based control (14). Subsequently, the adaptive neural network control (18) with the state feedback is evaluated. Finally, we conduct the simulation carrying on the comparison of PD controller.

4.1. *Model Based Control*

For the model based control, the initial conditions and the control parameters are chosen as $\eta(0) = [3.4, 15, 0.08]$, $\upsilon(0) = [20, -1.6, -2.9]$, $K_1 = \text{diag}[1, 50, 0.1]$, $K_2 = \text{diag}[40, 400, 10]$, $\Gamma_1 = 50I$, $\Gamma_2 = 100I$, $\Gamma_3 = 200I$, $\sigma_1 = 0.01$, $\sigma_2 = 0.01$, $\sigma_3 = 0.01$. To guarantee the state constraints $|x_1| < k_{c1} = [44.6, 15.7, 1.564]^T$, we can choose the constraints of z_1 will be $k_a = k_{c1} - X_0 = [4.6, 1.7, 0.17]^T$. In the same reason, we can proposed $|x_2|$ and $k_b = [5.8, 0.5, 0.2]$ as above.

The tracking performance of the closed-loop system for the vessel are given in Figs. 2 and 4. From the two figures, we can obtain that all the x_1 and x_2 can successfully track the desired trajectory. According the Figs. 3 and 5 we can state the system errors are converging to a small value close to zero. The corresponding control inputs are given in Fig. 6.

Figs. 7-11 show the results without the constraints in the same conditions. Fig. 7 is the comparison between the ideal trajectory and actual trajectory. The tracking error z_1 is shown in Fig. 8, and the tracking error z_2 is shown in Fig. 10. The control input τ is proposed in Fig. 11. Comparison the Fig. 8 and Fig. 3, we can obtain that our control design is effective.

4.2. *Adaptive Neural Network Control*

For adaptive neural network control with the state feedback. according to controller 18. The control objectives are to make the state of the system x_1 and x_2 track the ideal trajectory x_{1d} and x_{2d}, then guaranteeing the state constraints $|x_1| < k_{c1} = [44.6, 15.7, 1.564]^T$.

The reference trajectories satisfy $-X_0 \leq x_{1d} \leq X_0$ and $-Y_0 \leq x_{2d} \leq Y_0$. we can let $X_0 = [44.6, 15.7, 1.564]^T$, then we can obtain the constraints of z_1 will be $k_a = k_{c1} - X_0 = [4.6, 1.7, 0.17]^T$. Similarly, we can obtain $|x_2|$ and k_b in the same method as above.

We choose the parameters as $K_1 = \text{diag}[50, 20, 0.1]$, $K_2 = \text{diag}[40, 400, 10]$, $K_3 = \text{diag}[100, 400, 800]$, $\Gamma_1 = 50I$, $\Gamma_2 = 100I$, $\Gamma_3 = 200I$.

The simulation results are shown in Figs. 12-16. The Fig. 12 shows that the state x_1 can successful track the desired trajectory. From Fig. 13. we can know the tracking error is converging to a small value that close to zero. In Fig. 14, we can see that the x_2 tracks the desired trajectory with a high accuracy. The tracking error z_2 is proposed in Fig. 15, and the control input τ is shown in Fig. 16.

Figs. 17-21 show the results without the constraints in the same initial conditions. Fig. 17 is the comparison between the ideal trajectory and actual trajectory. The tracking error z_1 is shown in Fig. 18, and the tracking error z_2 is shown in Fig. 20. The control input τ is proposed in Fig. 21.

4.3. *PD Control*

The PD control law is designed as: $\tau = -K_p z_1 - K_d \dot{z}_1$. With all parameters are the same as the NN control, the terms of PD are added to the simulation: $K_p = \text{diag}[10, 20, 10]$, $K_d = \text{diag}[20, 50, 45]$.

The results of the simulation are shown in Figs. 24-26. It can be seen that, the errors of the PD control are larger than the NN control when the parameters of the system are unknown, because of the neural network learning ability. From Figs. 23 and 25, we can also obtain that the tracking efficiency are not as good as NN control, and the constraints are violated.

From above three cases. The performance of the proposed control (NN control) has been illustrated through the results of the simulation, which show the tracking of the trajectory is achieved without transgression of the constrained space.

5. Conclusion

In this paper, we consider the control design for a general class of marine surface vessels with full-state constraints and unknown parameters using the barrier Lyapunov function and neural networks. We have theoretically established that under the proposed control laws, the signals of the closed loop system are semiglobally uniformly bounded (SGUB), the asymptotic tracking is achieved, and the multiple state constraints would never be violated. Simulation results confirmed the effectiveness of the proposed design techniques.

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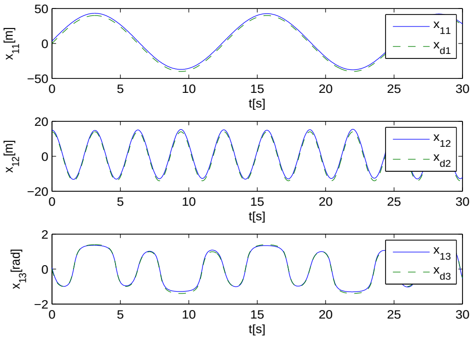

Figure 2. Comparison between x_1 and x_d of model based control.

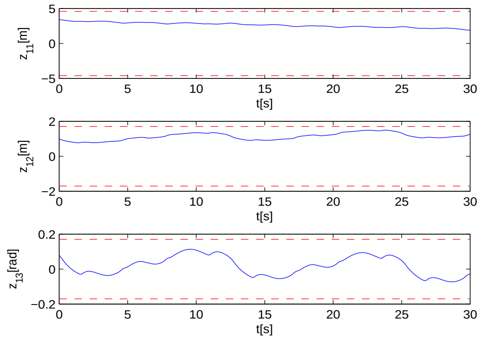

Figure 3. Tracking error z_1 of model based control.

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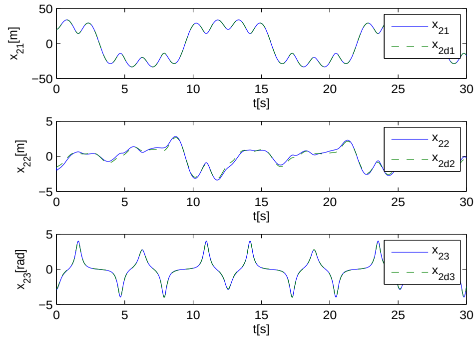

Figure 4. Comparison between x_2 and x_d of model based control.

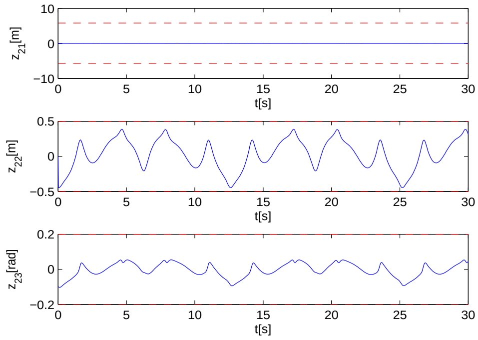

Figure 5. Tracking error z_2 of model based control.

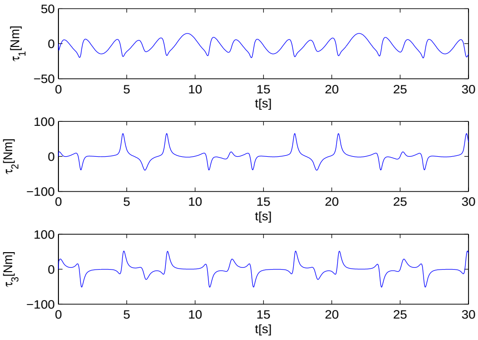

Figure 6. Control input τ of model based control.

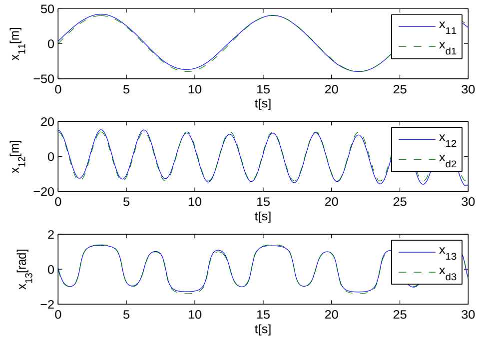

Figure 7. Comparison between x_1 and x_d without constraints of model based.

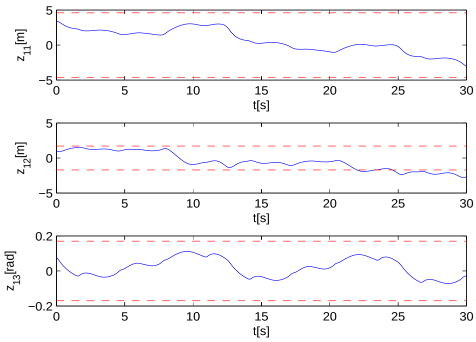

Figure 8. Tracking error z_1 without constraints of model based.

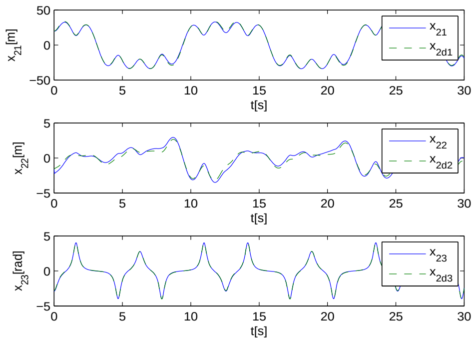

Figure 9. Comparison between x_2 and x_{2d} without constraints of model based.

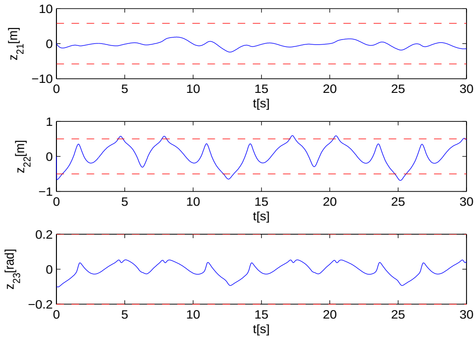

Figure 10. Tracking error z_2 without constraints of model based.

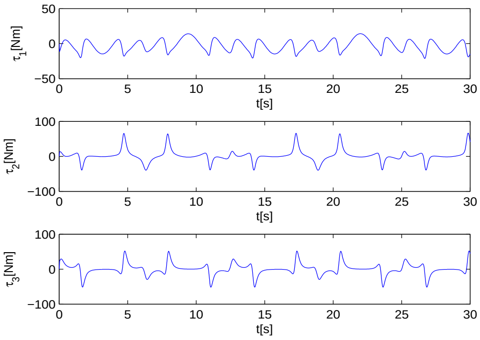

Figure 11. Control input τ without constraints of model based.

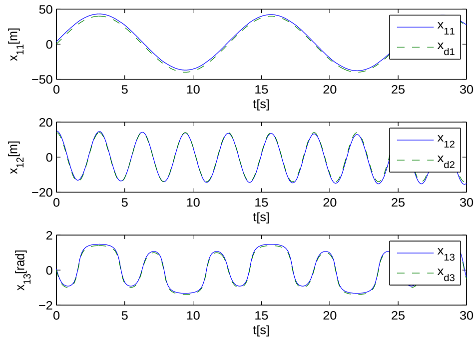

Figure 12. Comparison between x_1 and x_d of NN control.

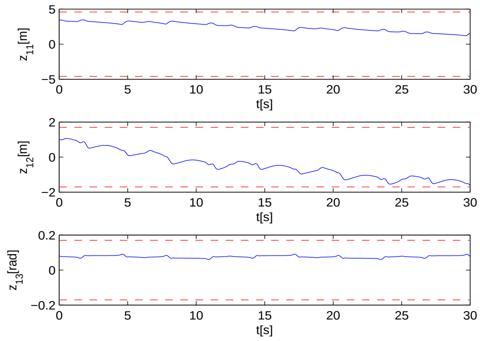

Figure 13. Tracking error z_1 of NN control.

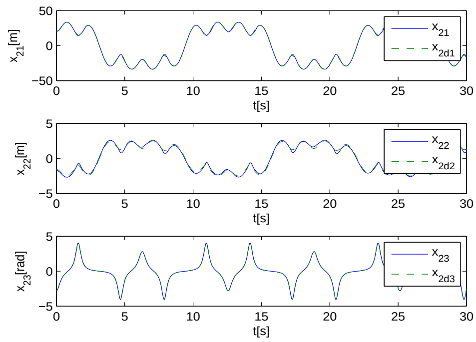

Figure 14. Comparison between x_2 and x_{2d} of NN control.

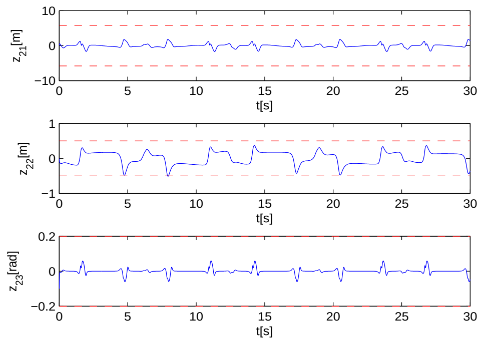

Figure 15. Tracking error z_2 of NN control.

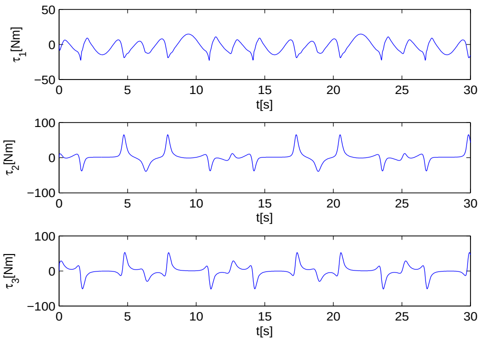

Figure 16. Control input τ of NN control.

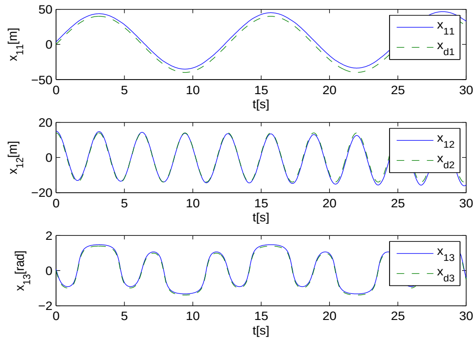

Figure 17. Comparison between x_1 and x_d without constraints of NN control.

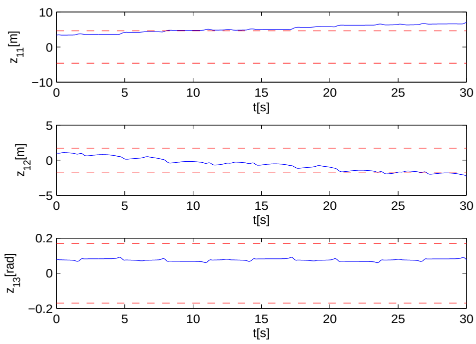

Figure 18. Tracking error z_1 without constraints of NN control.

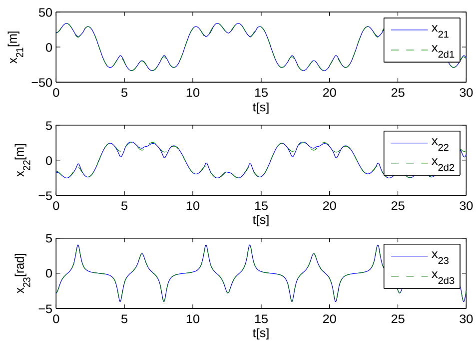

Figure 19. Comparison between x_2 and x_{2d} without constraints of NN control.

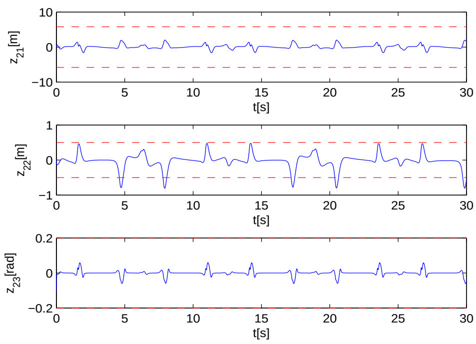

Figure 20. Tracking error z_2 without constraints of NN control.

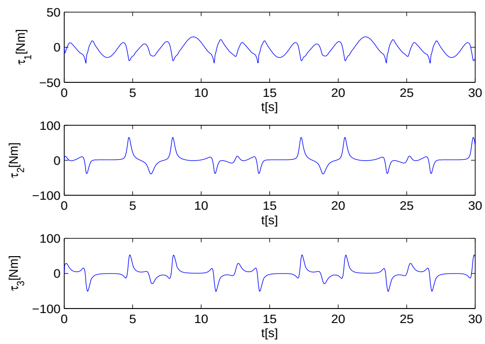

Figure 21. Control input τ without constraints of NN control.

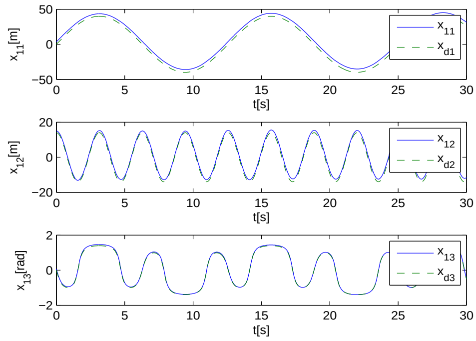

Figure 22. Comparison between x_1 and x_{1d} without constraints of PD control.

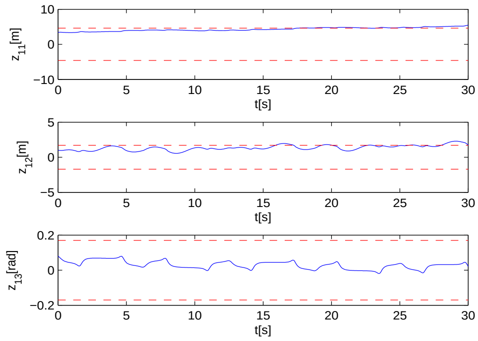

Figure 23. Tracking error z_1 of PD control.

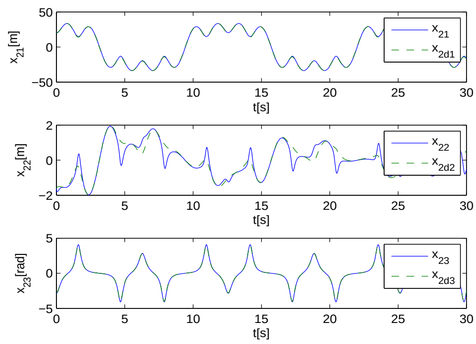

Figure 24. Comparison between x_2 and x_{2d} without constraints of PD control.

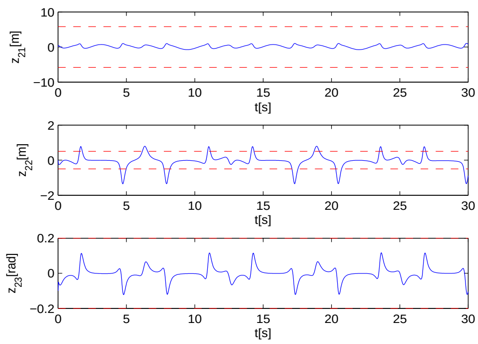

Figure 25. Tracking error z_12 of PD control.

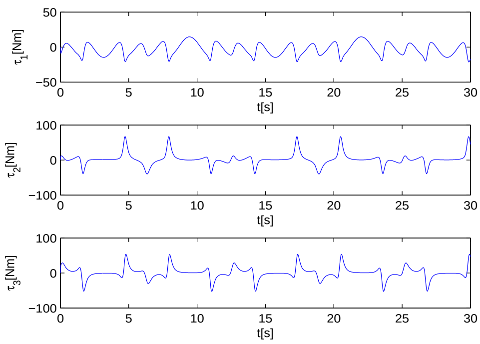

Figure 26. Control input τ without constraints of PD control.