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Adaptive Fuzzy Control for a Marine Vessel with Time-varying Constraints

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Abstract: An adaptive fuzzy neural network control scheme is proposed for a marine vessel with time-varying constraints, guaranteed transient response and unknown dynamics. A series of continuous constraint functions are introduced to shape the motion of a marine vessel. To deal with the constraint problems and transient response problems, an asymmetric time-varying barrier Lyapunov function is designed to ensure that the system states are upper bounded by the considered constraint functions. Fuzzy neural networks (FNNs) are constructed to identify the unknown dynamics. Considering existing approximation errors when FNNs approximating the unknown dynamics, an adaptive term is designed to compensate the approximation errors in order to obtain accurate control. Via Lyapunov stability theory, it has been proved that all the states in the closed-loop system are uniformly bounded ultimately without violating the corresponding prescribed constraint region. Two comparative simulations are carried out to verify the effectiveness of the proposed control.

1 Introduction

Recently, some advanced control schemes have been widely used and obtained a better control effect in modern offshore engineering applications [1]. With the development of maritime trade, the importance of the marine vessel and accurate control of a marine vessel is becoming increasingly prominent [2–6]. But traditional control schemes like PID control hardly satisfy the requirement of modern navigation safety as the complexity of control tasks increases for a marine vessel. By analysing the cause of the current marine vessel collision accidents, it is found that the inaccurate traveling control over the desired trajectory accounts for these accidents. And aggressive nature changes in the marine environment may result in marine vessel collision accidents, therefore a more accurate controller is of greater importance to the safety of the marine vessel. In recent years, many researchers have tried to employ neural network control [7–10], optimal control [11–14], robust control [15, 16] etc., to achieve the accurate control of some complicated systems in an intelligent and automatical form. If there exists an adaptive control constraining the motion of a marine vessel in a prescribed region, marine vessel collision accidents may decrease. To obtain such an adaptive control, fuzzy neural networks and barrier Lyapunov functions are utilized.

There often exist unmodeled dynamics and unknown parameters, thus it is very difficult to design an accurate controller satisfying the requirement of control performance. As we know, neural networks have been considered as a powerful tool in control and applications [17–19]. In [20, 21], the unknown marine vessel dynamics are identified by appropriate neural network structures. Neural network control can simulate the function of human to learn about the system they are controlling online such that system performance can be improved automatically. However, neural network control is not straightforward to extract comprehensible rules from the neural network's structure. In [22], in order to demand linguistic rules instead of learning data as prior knowledge, a fuzzy system based on the current output error and its time derivative is adopted to determine the value of control parameters. The approach has been shown to be effective in tracking a prescribed desired trajectory. However, it does not have any automatic learning capabilities to handle the uncertainty. After that, some research results have incorporated fuzzy techniques into neural network structure in order to obtain learning capabilities [23]. Furthermore, fuzzy neural networks are hybrid intelligent systems that combine advantages of both fuzzy systems and neural networks. As a result, the combination of the two techniques can not only avoid the lack of interpretability for neural networks but also enhance learning capabilities of fuzzy systems. In [24–26], the recognizing capability of fuzzy neural networks is employed to approximate the unknown system dynamics, which releases the need of accurate system information. In [27], an adaptive fuzzy neural network control is proposed for a constrained robot such that uniform boundedness is guaranteed. That strategy can reduce online computation load by using few adjustable parameters. By the research work mentioned-above, fuzzy neural networks can unite the advantage of both neural networks and fuzzy system, exclude their disadvantage. But the previous works [20, 21] don't consider the effect of time-varying constraints or guaranteed transient response performance for a marine vessel. Consequently, adaptive fuzzy neural network control should further be developed for a marine vessel with time-varying constraints and guaranteed transient response performance.

State constraints are very general in most marine vessel systems, and violation of these constraints during operation may lead to great performance degradation, safety issue, etc. And constraint control on system states can make the motion of the marine vessel remain in a small prescribed neighborhood of the reference trajectory, which further improves the tracking accuracy and may decrease the marine vessel collision accidents. It has been proved in [28–30] that barrier Lyapunov function has the ability to prevent the violation of constraints. In [31], output constraints are guaranteed by constructing an asymmetric time-varying barrier Lyapunov function for nonlinear systems. [32], based on the barrier Lyapunov function, the authors design a controller for unmanned aerial vehicles with full-state constraints. In [33], the barrier Lyapunov function is designed to prevent the violation of output constraints for a flexible string system. In [34], the symmetric barrier Lyapunov function is chosen to solve the control problems of the marine vessel with multiple output constraints. Thought full-state constraints or output constraints have been solved successfully for the marine vessel in [32–34], these constraints are constant constraints. However, in most situations, a marine vessel is subject to the wind, the wave loads and the ocean currents [5, 6], which would lead to a result that constant constraints hardly satisfy the requirement of engineering. Therefore, time-varying constraints of a marine vessel can meet the real demand better and should be further guaranteed. From this point, the control scheme in [32–34] is conservative. To overcome this conservatism, as the improvement we will develop an adaptive fuzzy neural network control for a marine vessel with time-varying constraints and guaranteed transient response performance.

Motivated by above observations, this paper will propose an adaptive fuzzy neural network control for a marine vessel with time-varying constraints and guaranteed transient response performance. Firstly, to obtain the prescribed transient response performance and prevent the violation of time-varying output constraints, a series of continuous constraint functions are introduced to shape the motion of the marine vessel. Meanwhile, the asymmetric barrier Lyapunov functions are introduced to ensure that the motion of the marine vessel is always upper bounded by the constraint functions. By the symmetric barrier Lyapunov functions, the velocity constraint can be guaranteed. Secondly, adaptive fuzzy neural networks are constructed to identify the unknown system dynamics and an auxiliary adaptive term is designed to compensate the approximation error of fuzzy neural networks. Finally, by combining the above procedure, an adaptive fuzzy neural network control is proposed. We introduce a series of new continuous constraint functions which converge to the exponential decay function as time intends to zero and the sine function as time approaches infinite, while the constraint functions considered in [20, 35, 36] only converge to constants as time approaches infinite. As time approaches infinite, the constraint functions considered in our paper can be considered as the time-varying output constraint functions and from the standpoint of actual motion control of a marine vessel, the time-varying constraints are more general than constant constraints. In the previous works [17–27, 37–40], the obtained design policy is based on an assumption that the approximation error of fuzzy neural networks or neural networks can converge to any small neighborhood of zero, however this assumption isn't always satisfied in the early stages of adaptation, which may cause poor tracking performance and even instability. To further solve this problem existing in [17–27, 37–40], we design an adaptive term to compensate the approximation error of fuzzy neural networks such that more accurate control can be obtained. In this paper, with respect to the traditional barrier Lyapunov functions used in [32–34], the asymmetric ln-type barrier Lyapunov function is designed to deal with the guaranteed transient response performance and time-varying output constraints, and fuzzy neural network control is utilized to approximate the unknown system dynamics. This type of proposed control is suitable for accurate trajectory tracking and objection manipulation.

Comparing with the previous works, the main contributions of this paper are summarized as follows: 1) A series of new continuous constraint functions are introduced to shape the motion of the marine vessel. By combining the asymmetric time-varying barrier Lyapunov function technique, guaranteed transient response and time-varying output constraints can be obtained. 2) Adaptive fuzzy neural networks are constructed to identify the unknown system dynamics, which releases the need of accurate system information. 3) Adaptive parameters which update online depending on tracking errors are designed to compensate the approximation error of FNNs such that under the action of the proposed control, the system would have a more accurate tracking performance.

2 Problem Formulation and Preliminaries

2.1 Problem Formulation

The motion and state variables of a single point mooring system are defined and gauged relative to the earth-fixed frame and the body-fixed frame, respectively. As shown in Fig. 1, (x_e, y_e) stands for that earth-fixed frame whose origin is located at the connection of the mooring line and the mooring terminal. The fixed body frame, expressed as (x_d, y_d), is taped to the vessel body, and its origin is consistent with the center of gravity of the moored vessel. The x_d axis is directed from rear to fore along the longitudinal axis of the marine surface vessel, and the y_d axis is directed to starboard. The

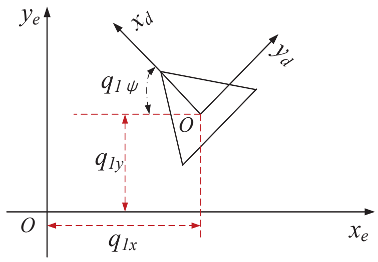

Fig. 1: Geometric figure of the marine surface vessel system.

dynamics [21, 41] of the marine vessel is expressed as

$$\begin{aligned}\dot{q}_1 &= J(q_1)q_2\\ M\dot{q}_2 + C(q_2)q_2 + D(q_2)q_2 + g(q_1) &= F\end{aligned} \tag{1}$$

where $q_1 = [q_{1x}, q_{1y}, q_{1\psi}] \in \mathbb{R}^3$ denotes the Earth-frame positions and heading. $F \in \mathbb{R}^3$ stands for the control input. $q_2 = [q_{2x}, q_{2y}, q_{2\psi}]^T \in \mathbb{R}^3$ denotes the velocity of a marine vessel. $M \in \mathbb{R}^{3\times3}$ denotes the symmetric positive definite inertia matrix. $C(q_2) \in \mathbb{R}^{3\times3}$ denotes the Centripetal and Coriolis torque, and $D(q_2) \in \mathbb{R}^{3\times3}$ denotes the damping matrix. $g(q_1) \in \mathbb{R}^3$ denotes the restoring forces resulted by gravity force, ocean currents, and floatage. $J(q_1) \in \mathbb{R}^{3\times3}$ is the transformation matrix and assumed to be nonsingular, and $J(q_1)$ is expressed as

$$J(q_1) = \begin{bmatrix} \cos q_{1\psi} & -\sin q_{1\psi} & 0\\ \sin q_{1\psi} & \cos q_{1\psi} & 0\\ 0 & 0 & 1\end{bmatrix} \tag{2}$$

Define $x_1 = q_1, x_2 = q_2$, (1) can be expressed as in the state-space form

$$\begin{aligned}\dot{x}_1 &= J(x_1)x_2\\ \dot{x}_2 &= M^{-1}[F - C(x_2)x_2 - D(x_2)x_2 - g(x_1)]\end{aligned} \tag{3}$$

The control objective in this paper is to design an adaptive FNN controller for a marine vessel such that a marine vessel can achieve accurate trajectory tracking control and all the states in the closed-loop system are uniformly bounded ultimately without violating the corresponding prescribed constraint region.

2.2 Preliminaries

Lemma 1. *[34] In this paper, a time-varying barrier Lyapunov function is introduced to cope with time-varying constraint problems. A* ln*-type time-varying barrier Lyapunov function is presented as*

$$V_f = \ln\frac{1}{1-\varpi^2}, \quad |\varpi| < 1 \tag{4}$$

which indicates that V_f is a positive function over the set $|\varpi| < 1$. The following inequality holds for $\varpi \in \mathbb{R}$ in the interval $|\varpi| < 1$.

$$\ln\frac{1}{1-\varpi^2} \le \frac{\varpi^2}{1-\varpi^2} \tag{5}$$

Property 1. *[42] $M \in \mathbb{R}^{n\times n}$ is a positive and symmetric matrix. $\lambda_{\min}$ and $\lambda_{\max}$ stand for minimum and maximum eigenvalues of M, respectively. The following inequality holds:*

$$\lambda_{\min}||x||^2 \le x^T M x \le \lambda_{\max}||x||^2, \quad \forall x \in \mathbb{R}^n \tag{6}$$

A function $N(\eta)$ is called a Nussbaum-type function which satisfies

$$\lim_{s\to\infty} \sup \frac{1}{s}\int_0^s N(\eta)d\eta = +\infty \quad (7)$$

$$\lim_{s\to\infty} \inf \frac{1}{s}\int_0^s N(\eta)d\eta = -\infty \quad (8)$$

Commonly Nussbaum functions include: $k^2\cos(k)$, $k^2\sin(k)$, $k\cos(k)$ and $k\sin(k)$. In this paper, $k\cos(k)$ is exploited. The following Lemma will be employed in the control design.

Lemma 2. *[27] $\eta(\cdot)$ and $V(\cdot)$ are smooth functions defined in the interval $[0, t_f)$ with $V(t) > 0$, $\forall t \in [0, t_f)$. $N(\eta) = \eta\cos(\frac{\pi}{2}\eta)$ is a smooth Nussbaum-type function. If the following inequality holds:*

$$V(t) \le \kappa_1 e^{-\kappa t} + e^{-\kappa t}\int_0^t g(\tau)N(\eta)\dot{\eta}e^{\tau t}d\tau, \quad \forall t \in [0, t_f) \quad (9)$$

where κ, κ_1 are positive constants. $g(t)$ is a time-varying function taking value in the unknown interval $I_1 := [l^-, l^+]$, where $0 \in I_1$. Then, $V(t)$ and $\int_0^t g(\tau)N(\eta)\dot{\eta}e^{\tau t}d\tau$ are bounded on $[0, t_f)$.

2.3 *Fuzzy Neural Networks*

A fuzzy system consists of four parts: the knowledge base, the fuzzifier, the fuzzy inference engine working on fuzzy rules, and the defuzzifier [43]. Consider l fuzzy IF-THEN rules $\mathbb{R}^{(k)}$: If x_1 is A_1^k and $\cdots$ and x_n is A_n^k, then y is $W^k, k = 1, \cdots, l$, where $\mathbb{R}^{(k)}$ denotes the k-th rule, $1 \le k \le l$, $(x_1, x_2, \cdots, x_n)^T \in \mathbb{U} \subset \mathbb{R}^n$, and $y \in \mathbb{R}$ are the linguistic variables that are associated with the inputs and output of the fuzzy logic system, respectively, and A_i^k and W^k denote the fuzzy sets in $\mathbb{U}$ and $\mathbb{R}$. The fuzzy logic system performs a nonlinear mapping from $\mathbb{U}$ to $\mathbb{R}$. In this paper, the fuzzy logic system is

$$y(x) = \frac{\sum_{k=1}^{l} y_k(\Pi_{i=1}^n \mu_{A_i^k}(x_i))}{\sum_{k=1}^{l}(\Pi_{i=1}^n \mu_{A_i^k}(x_i))} \quad (10)$$

where $x = [x_1, x_2, \cdots, x_n]^T$ and $\mu_{A_i^k}(x_i)$ is the membership function of linguistic variable x_i with $\mu_{A_i^k}(x_i) = \exp[-\frac{(x_i - c_{ik}^2)}{\sigma_{ik}^2}]$. Weight vectors and fuzzy basis function vectors are defined, respectively, as $\theta = [y_1, y_2, \cdots, y_l]^T$ and $\phi(x, c, \sigma) = [s_1, s_2, \cdots, s_l]^T$, where $s_k = \frac{\prod_{i=1}^n \mu_{A_i^k}(x_i)}{[\sum_{k=1}^{l}\prod_{i=1}^n \mu_{A_i^k}(x_i)]}$, $c = [c_1^T, c_2^T, \cdots, c_n^T]^T$ and $\sigma = [\sigma_1^T, \sigma_2^T, \cdots, \sigma_n^T]^T$. Therefore, (10) can be represented as

$$y = \theta^T\phi(x, c, \sigma) \quad (11)$$

It has been proven that the fuzzy logic system (11) has the capacity to approximate any given real continuous functions over a compact set to any degree of accuracy. Therefore, we have the following approximation for the unknown nonlinear function $f_i(x_i)$, $i = 1, 2, \cdots, n$.

$$f_i(x_i) = \theta_i^{*T}\phi(x_i) + \epsilon_i \quad (12)$$

where θ_i^{*T} is an unknown constant parameter vector, $\phi(x_i)$ is the fuzzy basis function and ϵ_i is the approximation error, which satisfies $\max_{Z\in\Omega_Z} ||\epsilon_i|| < \epsilon_i^*$, where $\epsilon_i^* > 0$ is unknown bound [44].

3 Control Design

Before starting to control design, the following tracking errors are defined.

$$z_1 = x_1 - x_d, \quad z_2 = x_2 - \alpha \quad (13)$$

where $z_1 = [z_{11}, z_{12}, z_{13}]^T$ denotes the position tracking error of a marine vessel, $z_2 = [z_{21}, z_{22}, z_{23}]^T$ stands for the velocity tracking error of a marine vessel. $\alpha = [\alpha_1, \alpha_2, \alpha_3]^T$ is a virtual controller which is designed later and aims to make error z_1 convergent. $x_d = [x_{d1}, x_{d2}, x_{d3}]^T$ is the reference trajectory of the marine vessel. Assume that $|x_{di}|$ is bounded, i.e., $|x_{di}| \le \mathcal{C}_i$ with $\mathcal{C}_i$ being a positive constant. Fig. 2 gives the system structure.

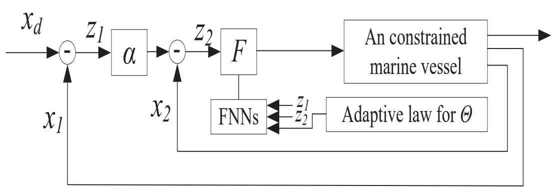

Fig. 2: System structure.

3.1 *Guaranteed Transient Response Performance and Time-varying Output Constraint Design*

To obtain the satisfactory tracking performance, especially transient response performance (overshoot, undershoot and convergence rate), we introduce a series of continuous constraint functions to shape the motion of the marine vessel as

$$\pi_{i,j} = (\pi_{0i,j} - \pi_{\infty i,j})e^{-\xi_{i,j}t} + \varrho_{i,j}\cos(\omega_{i,j}t) + \pi_{\infty i,j}$$
$$i = 1, 2, 3 \quad j = 1, 2 \quad (14)$$

in which $\pi_{i,j}$ is the jth ($j = 1$ denotes upper bound and $j = 2$ denotes lower bound) prescribed time-varying bound of ith error z_{1i}. $\varrho_{i,j}$, $\pi_{0i,j}$, $\pi_{\infty i,j}$, $\xi_{i,j}$ and $\omega_{i,j}$ are known constants which determine the shape of error trajectories. It can be seen from

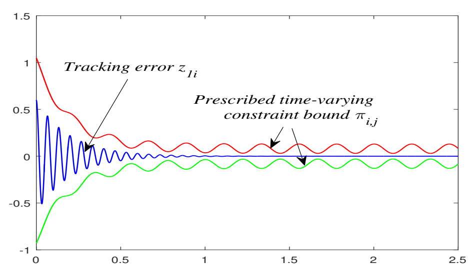

Fig. 3: Tracking error z_{1i} and prescribed time-varying constraint bound $\pi_{i,j}$

Fig. 3 that $(\pi_{0i,j} - \pi_{\infty i,j})e^{-\xi_{i,j}t} \gg \varrho_{i,j}\cos(\omega_{i,j}t) + \pi_{\infty i,j}$ is obtained by choosing appropriate parameters as $t \to 0$, in this case $\pi_{i,j} \approx (\pi_{0i,j} - \pi_{\infty i,j})e^{-\xi_{i,j}t}$, which shows that $\pi_{i,j}$ can shape the satisfactory transient response. Similarly, as $t \to \infty$, $(\pi_{0i,j} - \pi_{\infty i,j})e^{-\xi_{i,j}t} \ll \varrho_{i,j}\cos(\omega_{i,j}t) + \pi_{\infty i,j}$, thus it follows that $\pi_{i,j} \approx \varrho_{i,j}\cos(\omega_{i,j}t) + \pi_{\infty i,j}$, from which we know that time-varying output constraints can be guaranteed as $t \to \infty$. In other words, (14) not only guarantees the satisfactory transient response performance, but also prevents the violation of time-varying output constraints.

Remark 1. *In [20, 35, 36], control design mainly focuses on the transient response performance, but the disadvantage is that as* $t \to \infty$*, the considered constraint functions corresponding to (14) converge to a constant, this point is very conservative. To overcome this conservatism, we introduce a series of novel continuous constraint function given by (14) and the constraint function (14) will converge to time-varying function* $\varrho_{i,j}\cos(\omega_{i,j}t) + \pi_{\infty i,j}$ *as* $t \to \infty$*. From engineering standpoint, time-varying constraints are more general than constant constraints.*

Then, the control objective in this section is to design a proper virtual controller such that tracking error z_1 can satisfy the prescribed performance shown in Fig. 3. To guarantee the prescribed performance, the following transformation error is introduced and will be used in the later design.

$$\varpi_a = \left[\frac{z_{11}}{\pi_{1,2}}, \frac{z_{12}}{\pi_{2,2}}, \frac{z_{13}}{\pi_{3,2}}\right]^T, \ \varpi_b = \left[\frac{z_{11}}{\pi_{1,1}}, \frac{z_{12}}{\pi_{2,1}}, \frac{z_{13}}{\pi_{3,1}}\right]^T,$$
$$\varpi_i = (1 - h_i(z_{1i}))\varpi_{a,i} + h_i(z_{1i})\varpi_{b,i}, \ \ i = 1, 2, 3 \tag{15}$$

where π_{i1}, π_{i2} are prescribed upper and lower bounds of error z_{1i}, respectively. $\varpi_{a,i}, \varpi_{b,i}$ are ith element of ϖ_a, ϖ_b, respectively, $h_i(z_{1i})$ is defined as a switching function given by

$$h_i(z_{1i}) = \begin{cases} 1, & z_{1i} \geq 0 \\ 0, & z_{1i} < 0 \end{cases} \tag{16}$$

In the interval $0 < \varpi_{a,i} < 1$ or $0 < \varpi_{b,i} < 1$, an asymmetric time-varying barrier Lyapunov function is constructed as

$$V_1 = \sum_{i=1}^{3}\left(\frac{h_i}{2}\ln\frac{1}{1-\varpi_{b,i}^2} + \frac{1-h_i}{2}\ln\frac{1}{1-\varpi_{a,i}^2}\right) \tag{17}$$

Differentiating V_1 with respect to time yields

$$\dot{V}_1 = \sum_{i=1}^{3}\left(\frac{h_i}{1-\varpi_{b,i}^2}\varpi_{b,i}\dot{\varpi}_{b,i} + \frac{1-h_i}{1-\varpi_{a,i}^2}\varpi_{a,i}\dot{\varpi}_{a,i}\right) \tag{18}$$

According to the definitions of $\varpi_{a,i}, \varpi_{b,i}$, we have

$$\begin{aligned}\dot{V}_1 =& \sum_{i=1}^{3}\left(\frac{\varpi_i^2}{(1-\varpi_i^2)z_{1i}}\dot{z}_{1i}\right) + \sum_{i=1}^{3}\left(\frac{(1-h_i)\varpi_{a,i}^2}{(1-\varpi_{a,i}^2)}\frac{\dot{\pi}_{i,1}}{\pi_{i,1}}\right) \\ &+ \sum_{i=1}^{3}\left(\frac{h_i\varpi_{b,i}^2}{(1-\varpi_{b,i}^2)}\frac{\dot{\pi}_{i,2}}{\pi_{i,2}}\right)\end{aligned} \tag{19}$$

Define control matrix Q as

$$Q = \left[\frac{\varpi_1^2}{(1-\varpi_1^2)z_{11}}, \frac{\varpi_2^2}{(1-\varpi_2^2)z_{12}}, \frac{\varpi_3^2}{(1-\varpi_3^2)z_{13}}\right]^T \tag{20}$$

Therefore, we have

$$\begin{aligned}\dot{V}_1 =& Q^T\dot{z}_1 + \sum_{i=1}^{3}\left(\frac{(1-h_i)\varpi_{a,i}^2}{(1-\varpi_{a,i}^2)}\frac{\dot{\pi}_{i,1}}{\pi_{i,1}}\right) \\ &+ \sum_{i=1}^{3}\left(\frac{h_i\varpi_{b,i}^2}{(1-\varpi_{b,i}^2)}\frac{\dot{\pi}_{i,2}}{\pi_{i,2}}\right)\end{aligned} \tag{21}$$

Remark 2. *For ith element* $\frac{\varpi_i^2}{(1-\varpi_i^2)z_{1i}}$ *of matrix Q, the following two cases are considered to show the singularity of* $\frac{\varpi_i^2}{(1-\varpi_i^2)z_{1i}}$*. If* $z_{1i} \geq 0$*,* $\frac{\varpi_i^2}{(1-\varpi_i^2)z_{1i}}$ *is rewritten as* $\frac{z_{1i}}{\pi_{i,1}^2 - z_{1i}^2}$*, and* $\frac{z_{1i}}{\pi_{i,1}^2 - z_{1i}^2}$ *is well-defined in the prescribed region* $z_{1i} < \pi_{i,1}$*. If* $z_{1i} < 0$*, the results are similar to above results. Therefore,* $\frac{\varpi_i^2}{(1-\varpi_i^2)z_{1i}}$ *is well-defined in the prescribed region* $\pi_{i,2} < z_{1i} < \pi_{i,1}, i = 1, 2, 3$*.*

Notice that motion $\dot{x}_1 = J(x_1)x_2$ and $z_1 = x_1 - x_d, z_2 = x_2 - \alpha$, thus $\dot{z}_1 = J(x_1)(z_2 + \alpha) - \dot{x}_d$. To further obtain virtual control α, substituting $\dot{z}_1$ into (21) yields

$$\begin{aligned}\dot{V}_1 =& Q^T(J(x_1)(z_2+\alpha) - \dot{x}_d) + \sum_{i=1}^{3}\left(\frac{(1-h_i)\varpi_{a,i}^2}{(1-\varpi_{a,i}^2)}\frac{\dot{\pi}_{i,1}}{\pi_{i,1}}\right) \\ &+ \sum_{i=1}^{3}\left(\frac{h_i\varpi_{b,i}^2}{(1-\varpi_{b,i}^2)}\frac{\dot{\pi}_{i,2}}{\pi_{i,2}}\right)\end{aligned} \tag{22}$$

The virtual control α is proposed as follows

$$\alpha = J^+(x_1)(\dot{x}_d - K_1 z_1 - \gamma z_1) \tag{23}$$

where $J^+(x_1)$ is the Moore-Penrose pseudoinverse of $J(x_1)$, $K_1 = K_1^T$ is a positive definite gain matrix, γ_i is a positive constant satisfying

$$\gamma_i > \sqrt{\left(\frac{\dot{\pi}_{i,1}}{\pi_{i,1}}\right)^2 + \left(\frac{\dot{\pi}_{i,2}}{\pi_{i,2}}\right)^2}, \ \ i = 1, 2, 3 \tag{24}$$

and $\gamma = \mathrm{diag}[\gamma_1, \gamma_2, \gamma_3]$. Then, substituting virtual control α into (22) yields

$$\dot{V}_1 \leq -Q^T K_1 z_1 + Q^T J(x_1) z_2 \tag{25}$$

In the subsequent design, the coupling term $Q^T J(x_1)z_2$ will be removed.

Remark 3. *As can be observed from (17), a time-varying barrier function is integrated into the designed Lyapunov function. It is clear that* $|\varpi_{a,i}|, |\varpi_{b,i}|$ *cannot be greater than one. Combining (15), we can conclude that the prescribed performance shown in Fig. 3 is guaranteed. And by choosing appropriate parameters, the designer can obtain the satisfactory tracking performance.*

3.2 Adaptive Fuzzy Neural Network Control with Full-state Constraints

An adaptive FNN control scheme with self-learning ability will be presented to address full-state constraints and unknown dynamics for a marine vessel. The recognizing capacity of fuzzy neural networks is employed to identify the unknown plant of a marine vessel. In Guaranteed Transient Response Performance and Time-varying Output Constraint Design, tracking error z_1 has been constrained by the time-varying constraint region $\pi_{i,2} < z_{1i} < \pi_{i,1} (i = 1, 2, 3)$. Then, error z_2 should be constrained to satisfy $||z_2|| < b$, provided that $||z_2(0)|| < b$, with b being a positive constant, the detailed design is presented as follows.

Since there exist uncertainties in $M, C(x_2), D(x_2), g(x_1)$, a traditional non-adaptive controller based on error signals hardly achieves such a complicated control goal. FNNs have the ability to approximate these uncertainties [27, 45]. Therefore, the following unknown term is approximated by FNNs.

$$\theta^{*T}\phi(Z) + \epsilon(Z) = C(x_2)x_2 + D(x_2)x_2 + g(x_1) + M\dot{\alpha} \tag{26}$$

where $Z = [x_1^T, x_2^T, \alpha^T, \dot{\alpha}^T]$ is the input of FNNs. $\tilde{\theta}, \hat{\theta}, \theta^*$ are error weights, actual weights and optimal constant weights, respectively, and there is $\tilde{\theta} = \hat{\theta} - \theta^*$. $\epsilon(Z) = [\epsilon(Z)_1, \epsilon(Z)_2, \epsilon(Z)_3]^T$ denotes the unknown approximation error. Assume that $P^* = [P_1^*, P_2^*, P_3^*]^T$ stands for an unknown upper bound of $\epsilon(Z)$, namely

$$\sup\{|\epsilon(Z)_i|\} \leq P_i^*, \quad i = 1, 2, 3 \tag{27}$$

Define $\hat{P} = [\hat{P}_1, \hat{P}_2, \hat{P}_3]^T$ as an estimation value of P^*, $\tilde{P}$ denotes estimation errors satisfying $\tilde{P} = [\tilde{P}_1, \tilde{P}_2, \tilde{P}_3]^T = \hat{P} - P^*$, and in the subsequent design $\hat{P}$ will be used to compensate the FNN approximation error $\epsilon(Z)$. Then, an adaptive FNN controller is designed as

$$\begin{aligned} F = & - K_2 z_2 - \frac{K_3 z_2}{b^T b - z_2^T z_2} + \hat{\theta}^T \phi(Z) \\ & - \begin{bmatrix} \hat{P}_1 \tanh(\frac{z_{21}}{\delta}) \\ \hat{P}_2 \tanh(\frac{z_{22}}{\delta}) \\ \hat{P}_3 \tanh(\frac{z_{23}}{\delta}) \end{bmatrix} - J^T(x_1) Q \end{aligned} \tag{28}$$

where $K_2 = \text{diag}[k_{21}, k_{22}, k_{23}]$, δ is a small positive constant. To further improve the system performance, the updating laws of $\hat{\theta}, \hat{P}$ are designed as

$$\dot{\hat{\theta}}_i = -\Gamma_i[\phi(Z) z_{2i} + \sigma_i \hat{\theta}_i], \;\; i = 1, 2, 3 \tag{29}$$

$$\dot{\hat{P}}_i = \tanh(\frac{z_{2i}}{\delta}) z_{2i} - \sigma_{pi} \hat{P}_i, \;\; i = 1, 2, 3 \tag{30}$$

where $\Gamma_i = \Gamma_i^T$ is a positive gain matrix. σ_i, σ_{pi} are positive constants which improve the robustness of the system. By combining (3), (13) and (26), the following closed-loop error dynamics is obtained.

$$\dot{z}_1 = J(x_1)(z_2 + \alpha) - \dot{\alpha} \tag{31}$$

$$\dot{z}_2 = M^{-1}(F - \theta^{*T} \phi(Z) - \epsilon(Z)) \tag{32}$$

According to the closed-loop error dynamics (31) and (32), the following positive barrier Lyapunov function is defined in the interval $\|z_2\| < b$.

$$\begin{aligned} V_2 = & V_1 + \frac{1}{2} \ln \frac{1}{b^T b - z_2^T z_2} + \frac{1}{2} z_2^T M z_2 \\ & + \frac{1}{2} \sum_{i=1}^{3} \tilde{\theta}_i^T \Gamma_i^{-1} \tilde{\theta}_i^T + \frac{1}{2} \sum_{i=1}^{3} \tilde{P}_i^2 \end{aligned} \tag{33}$$

The derivative of V_2 with respect to time yields

$$\begin{aligned} \dot{V}_2 = & \dot{V}_1 + \frac{z_2^T \dot{z}_2}{b^T b - z_2^T z_2} + z_2^T M \dot{z}_2 + \sum_{i=1}^{3} \tilde{\theta}_i^T \Gamma_i^{-1} \dot{\hat{\theta}}_i \\ & + \sum_{i=1}^{3} \tilde{P}_i \dot{\hat{P}}_i \end{aligned} \tag{34}$$

Substituting (26)-(30) into (34) yields

$$\begin{aligned} \dot{V}_2 \leq & \dot{V}_1 + \frac{z_2^T \dot{z}_2}{b^T b - z_2^T z_2} - z_2^T K_2 z_2 - \frac{z_2^T K_3 z_2}{b^T b - z_2^T z_2} - Q^T \\ & \times J(x_1) z_2 + P^{*T} \begin{bmatrix} |z_{21}| - z_{21} \tanh(\frac{z_{21}}{\delta}) \\ |z_{22}| - z_{22} \tanh(\frac{z_{22}}{\delta}) \\ |z_{23}| - z_{23} \tanh(\frac{z_{23}}{\delta}) \end{bmatrix} + z_2^T \\ & \times \tilde{\theta}^T \phi(Z) - \sum_{i=1}^{3} \tilde{\theta}_i^T [\phi(Z) z_{2i} + \sigma_i \hat{\theta}_i] - \sum_{i=1}^{3} \tilde{P}_i \sigma_{pi} \hat{P}_i \end{aligned} \tag{35}$$

Note that the following inequalities hold in terms of the Young's inequality,

$$-\sum_{i=1}^{3} \sigma_i \tilde{\theta}_i^T \hat{\theta}_i \leq -\frac{\sigma_i}{2} \sum_{i=1}^{3} \tilde{\theta}_i^T \tilde{\theta}_i + \frac{\sigma_i}{2} \sum_{i=1}^{3} ||\theta_i^*||^2 \tag{36}$$

$$-\sum_{i=1}^{3} \tilde{P}_i \sigma_{pi} \hat{P}_i \leq -\frac{\sigma_{pi}}{2} \sum_{i=1}^{3} \tilde{P}_i^2 + \frac{\sigma_{pi}}{2} \sum_{i=1}^{3} P_i^{*2} \tag{37}$$

And the following inequality holds for any $\eta > 0$ and $z \in \mathbb{R}$ [46]

$$|z| - z \tanh(\frac{z}{\eta}) \leq \nu \eta \tag{38}$$

where ν is a constant satisfying $\nu = e^{-(\nu+1)}$, i.e., $\nu = 0.2785$. Therefore, there is

$$0 \leq P_i^*(|z_{2i}| - z_{2i} \tanh(\frac{z_{2i}}{\delta})) \leq 0.2785 P_i^* \delta, \quad i = 1, 2, 3 \tag{39}$$

, and

$$\begin{aligned} & P_1^*(|z_{21}| - z_{21} \tanh(\frac{z_{21}}{\delta})) + P_2^*(|z_{22}| - z_{22} \tanh(\frac{z_{22}}{\delta})) \\ & + P_3^*(|z_{23}| - z_{23} \tanh(\frac{z_{23}}{\delta})) \leq 0.2785 \delta (P_1^* + P_2^* + P_3^*) \\ & \leq 0.8355 \delta ||P^*|| \end{aligned} \tag{40}$$

Notice that

$$z_2^T \tilde{\theta}^T \phi(Z) = \sum_{i=1}^{3} \tilde{\theta}_i^T \phi(Z) z_{2i} \tag{41}$$

Considering Lemma 1, Property 1 and substituting (36), (37), (40), (41) into (35), we have

$$\begin{aligned} \dot{V}_2 \leq & -Q^T K_1 z_1 + \frac{z_2^T \dot{z}_2}{b^T b - z_2^T z_2} - z_2^T K_2 z_2 - \frac{z_2^T K_3 z_2}{b^T b - z_2^T z_2} \\ & - \frac{\sigma_i}{2} \sum_{i=1}^{3} \tilde{\theta}_i^T \tilde{\theta}_i + \frac{\sigma_i}{2} \sum_{i=1}^{3} ||\theta_i^*||^2 - \frac{\sigma_{pi}}{2} \sum_{i=1}^{3} \tilde{P}_i^2 \\ & + \frac{\sigma_{pi}}{2} \sum_{i=1}^{3} P_i^{*2} + 0.8355 \delta ||P^*|| \\ \leq & -\kappa_2 V_2 + C_2 + \frac{z_2^T \dot{z}_2}{b^T b - z_2^T z_2} \end{aligned} \tag{42}$$

where

$$\begin{aligned} \kappa_2 = \min \Bigg\{ & 2\lambda_{\min}(K_1), 2\lambda_{\min}(K_3), \frac{2\lambda_{\min}(K_2)}{\lambda_{\max}(M)}, \\ & \min_{i=1,2,3} \{ \frac{\sigma_i}{\lambda_{\min}(\Gamma_i^{-1})} \}, \min_{i=1,2,3} \{ \sigma_{pi} \} \Bigg\} \\ C_2 = & \sum_{i=1}^{3} \frac{\sigma_{pi}}{2} P_i^{*2} + \sum_{i=1}^{3} \frac{\sigma_i}{2} ||\theta_i^*||^2 + 0.8355 \delta ||P^*|| \end{aligned}$$

3.3 *Stability Analysis*

Multiply $e^{\kappa_2 t}$ on both sides of (42), one can obtain

$$\dot{V}_2 e^{\kappa_2 t} + \kappa_2 V_2 e^{\kappa_2 t} \leq C_2 e^{\kappa_2 t} + g(t) N(z_2) \dot{z}_2 e^{\kappa_2 t} \tag{43}$$

where

$$\begin{aligned} g(t) &= \frac{z_2^T}{(b^T b - z_2^T z_2) \cos(\frac{\pi \sum_{i=1}^{3} |z_{2i}|}{6b})} \\ N(z_2) &= \cos(\frac{\pi \sum_{i=1}^{3} |z_{2i}|}{6b}) \end{aligned}$$

Integrating (43) results in

$$V_2(t) \leq V_2(0) + \frac{C_2}{\kappa_2} + e^{-\kappa_2 t} \int_0^t g(\tau) N(z_2) \dot{z}_2 e^{\tau t} d\tau \tag{44}$$

It can be known from Lemma 2 that $\int_0^t g(\tau)N(z_2)\dot{z}_2 e^{\tau t} d\tau$ is bounded, i.e., $|\int_0^t g(\tau)N(z_2)\dot{z}_2 e^{\tau t} d\tau| \leq C_0$ with C_0 being a positive constant. Thus, we have $V_2(t) \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0$ on condition that $\kappa_2 > 0, C_2 > 0$. Then, the following theorem is employed to summarize the control design.

Remark 4. *$\sigma_i > 0, \sigma_{pi} > 0$ are the σ_i-modification and σ_{pi}-modification to prevent the estimation from drifting to large values in the presence of estimation errors [47]. Furthermore, it is easy to see that $\hat{\theta}_i \leq 0$, $\hat{P}_i \geq 0$ provided the updating laws (29) and (30), the non-negative initial values and $z_{2i} \geq 0$.*

Theorem 1. *For the marine vessel system given by (1) with the controller (28), updating laws (29) and (30), given that initial values of states are bounded, it can be concluded that all the system states are uniformly bounded ultimately without violating the corresponding constraints and the system output x_1 goes into a small neighborhood of the reference trajectory x_d. The following statements summarize the control design in detail.*

1) Tracking error z_1 is uniformly bounded ultimately and satisfies $\underline{C}_i \leq z_{1i} \leq \bar{C}_i$ for $\forall t > 0$. The time-varying output constraint can be guaranteed, namely $\underline{C}_i + x_{di} < x_{1i} < \bar{C}_i + x_{di}, i = 1, 2, 3$ for $\forall t > 0$, where $\underline{C}_i = \pi_{i,2}\sqrt{1 - e^{-2\rho}}$, $\bar{C}_i = \pi_{i,1}\sqrt{1 - e^{-2\rho}}$, $\rho = V_2(0) + \frac{C_2}{\kappa_2} + C_0$.

2) Tracking error z_2 is uniformly bounded ultimately and satisfies $||z_2|| \leq \sqrt{b^T b - e^{-2\rho}}$ for $\forall t > 0$. The constraint on x_2 can be guaranteed, i.e., $\|x_2\| < \sup\|\alpha\| + \sqrt{b^T b - e^{-2\rho}}$ for $\forall t > 0$.

Proof: It is known from (44) that $V_2(t) \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0$. Combining (33), we have

$$V_1 \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0 \tag{45}$$

$$\frac{1}{2}\ln\frac{1}{b^T b - z_2^T z_2} \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0 \tag{46}$$

For $z_{1i} \geq 0, i = 1, 2, 3$, we have

$$\frac{1}{2}\ln\frac{1}{1 - \varpi_{b,i}^2} \leq \sum_{i=1}^{3}\frac{1}{2}\ln\frac{1}{1 - \varpi_{b,i}^2} \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0 \tag{47}$$

thus

$$|\varpi_{b,i}| \leq \sqrt{1 - e^{-2\rho}}, \quad i = 1, 2, 3 \tag{48}$$

Since $\varpi_{b,i} = \frac{z_{1,i}}{\pi_{i,1}}$, we have

$$z_{1i} \leq \pi_{i,1}\sqrt{1 - e^{-2\rho}}, \quad i = 1, 2, 3 \tag{49}$$

For $z_{1i} < 0$, considering $\varpi_{a,i} = \frac{z_{1,i}}{\pi_{i,2}}$, we have

$$\pi_{i,2}\sqrt{1 - e^{-2\rho}} \leq z_{1i}, \quad i = 1, 2, 3 \tag{50}$$

Therefore,

$$\pi_{i,2}\sqrt{1 - e^{-2\rho}} \leq z_{1i} \leq \pi_{i,1}\sqrt{1 - e^{-2\rho}}, \quad i = 1, 2, 3 \tag{51}$$

Note that $z_1 = x_1 - x_d$, thus

$$\begin{aligned}\pi_{i,2}\sqrt{1 - e^{-2\rho}} + x_{di} &\leq x_{1i} \\ &\leq \pi_{i,1}\sqrt{1 - e^{-2\rho}} + x_{di}, i = 1, 2, 3\end{aligned} \tag{52}$$

For $\frac{1}{2}\ln\frac{1}{b^T b - z_2^T z_2} \leq V_2(0) + \frac{C_2}{\kappa_2} + C_0$, we have

$$||z_2|| \leq \sqrt{b^T b - e^{-2\rho}} \tag{53}$$

Similarly, we have

$$||x_2|| \leq \sup\|\alpha\| + \sqrt{b^T b - e^{-2\rho}} \tag{54}$$

The proof is completed.

4 Simulation Studies

The model used for simulation is the 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 [21]. The reference trajectories of x_1 are expressed as

$$\begin{cases} x_{1xd} = 0.5\sin(t) \\ x_{1yd} = 0.14\cos(2t) \\ x_{1\psi d} = \tan^{-1}(\frac{\dot{x}_{1xd}}{\dot{x}_{1yd}}) \end{cases} \tag{55}$$

The following two different cases are investigated for simulation studies. First, we examine the effectiveness of proposed control (28). Second, to better show superiority of the proposed control (28), PD control is implemented.

4.1 Adaptive FNN control

For the proposed control, control parameters are chosen as follows: $K_1 = \text{diag}[1, 1, 1]$, $K_2 = \text{diag}[1, 1, 1]$, $K_3 = \text{diag}[1, 1, 1]$, $\delta = 0.0001$. Updating law parameters are given as $\Gamma_1 = \Gamma_2 = \Gamma_3 = 50I_{7^6\times7^6}$, $\sigma_1 = \sigma_2 = \sigma_3 = 0.001$, $\sigma_{p1} = \sigma_{p2} = \sigma_{p3} = 0.001$. Initial values are given as $x_1(0) = [0.0031, 0.14501, 0.001]^T$, $x_2(0) = [0.4, 0, -1.4]^T$, $\hat{P}(0) = [0, 0, 0]$, and $\hat{\theta}_1(0) = \hat{\theta}_2(0) = \hat{\theta}_3(0) = [0, \ldots, 0]^T_{7^6\times1}$.

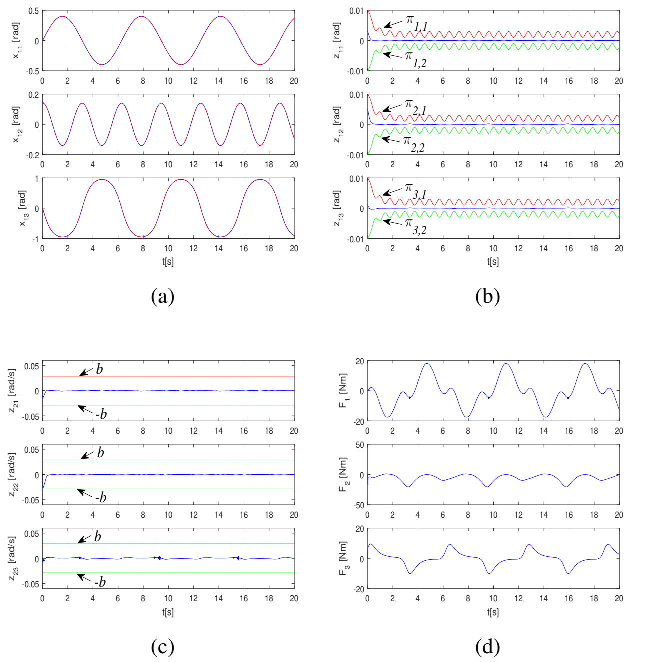

Fig. 4: (a) Tracking performance of variable x_1 with FNN control (solid blue: actual; dashed red: reference). (b) Tracking error $z_1 = x_1 - x_d$ with FNN control (red: upper constraint bound; blue: error; green: lower constraint bound). (c) Tracking error z_2 with FNN control (red: upper constraint bound; blue: error; green: lower constraint bound). (d) Control input F with FNN control.

For parameters of time-varying constraint function (14), upper bound parameters are given as follows, initial values $\pi_{01,1} = \pi_{02,1} = \pi_{03,1} = 0.01$, steady-state values $\pi_{\infty1,1} =$

$\pi_{\infty 2,1} = \pi_{\infty 3,1} = 0.002$, attenuation rate $\xi_{1,1} = \xi_{2,1} = \xi_{3,1} = 2$, amplitude of vibration $\varrho_{1,1} = \varrho_{2,1} = \varrho_{3,1} = 0.001$, and vibration frequency $\omega_{1,1} = \omega_{2,1} = \omega_{3,1} = 8$, and lower bound parameters are given as follows, initial values $\pi_{01,2} = \pi_{02,2} = \pi_{03,2} = -0.01$, steady-state values $\pi_{\infty 1,2} = \pi_{\infty 2,2} = \pi_{\infty 3,2} = 0.002$, attenuation rate $\xi_{1,2} = \xi_{2,2} = \xi_{3,2} = 2$, amplitude of vibration $\varrho_{1,2} = \varrho_{2,2} = \varrho_{3,2} = -0.001$, and vibration frequency $\omega_{1,2} = \omega_{2,2} = \omega_{3,2} = 8$. Velocity constraint bound b is set as $b = 0.0287$.

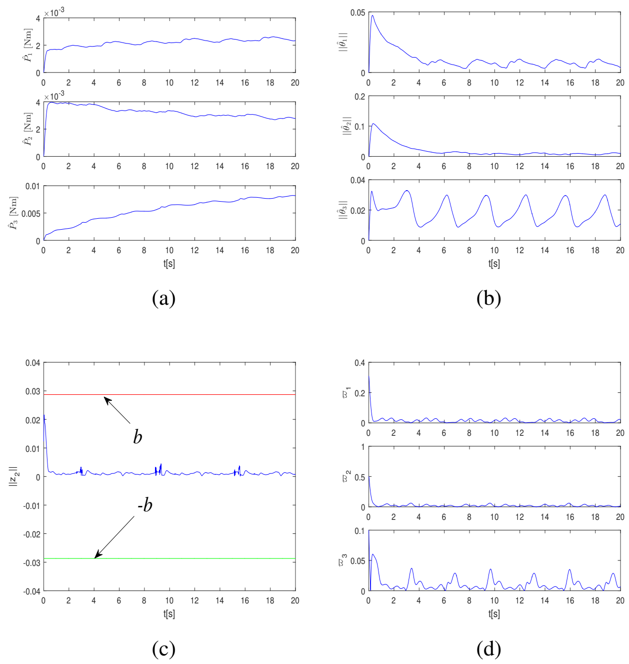

Fig. 5: (a) Adaptive parameter $\hat{P}$ with FNN control. (b) two-norm of FNN weights with FNN control. (c) $\|z_2\|$ with FNN control (red: upper constraint bound; blue: error; green: lower constraint bound). (d) transformation error ϖ.

Simulation results are given in Figs. 4-5. Fig. 4(a) illustrates reference trajectory x_d and actual trajectory x_1. From Fig. 4(a), we can see that x_1 can track reference trajectory x_d in desired accuracy. Fig. 4(b) states that tracking error z_1 remains in the prescribed time-varying constraint region ($\pi_{i,2} < z_{1i} < \pi_{i,1}, i = 1, 2, 3$) when the proposed control (28) is applied on the system (3), which also demonstrates that the introduced constraint function (14) is satisfactory, and the overshoot and stability time of z_1 are very small and satisfactory. In Fig. 5(d), transformation error ϖ is presented, and from this figure we clearly know that ϖ is less than one, which shows that tracking errors z_{1i} still remain in the prescribed time-varying constraint region $\pi_{i,2} < z_{1i} < \pi_{i,1}, i = 1, 2, 3$. Fig. 4(c) and 5(c) show error z_2 still remains in the predefined region $||z|| \leq b$. Fig. 4(d) gives control input F bounded by an unknown constant. Fig. 5(a) gives adaptive parameter $\hat{P}$ designed to compensate for the approximation error of FNNs. Fig. 5(b) presents two-norm of FNN weights which are bounded by an unknown constant. From the above discussions, we can know that Theorem 1 is reasonable.

4.2 PD Control

The PD controller is designed as follows

$$F = K_p z_1 + K_d \dot{z}_1 \tag{56}$$

where $K_p \in \mathbb{R}$ denotes the proportional gain, $K_d \in \mathbb{R}$ denotes the differential gain. To further demonstrate the advantage of the proposed control (28), five different gain parameters are set as follows, $K_p = K_d = -300$, $K_p = K_d = -500$, $K_p = K_d = -700$, $K_p = K_d = -900$ and $K_p = K_d = -1100$. Initial values are the same as ones in adaptive FNN control simulation. Simulation results are given in Fig. 6. In Figs. 6(a)-6(c), tracking error z_1 is plotted based on five different gain parameters. In Fig. 6(d), control input F based on five different gain parameters is presented, respectively.

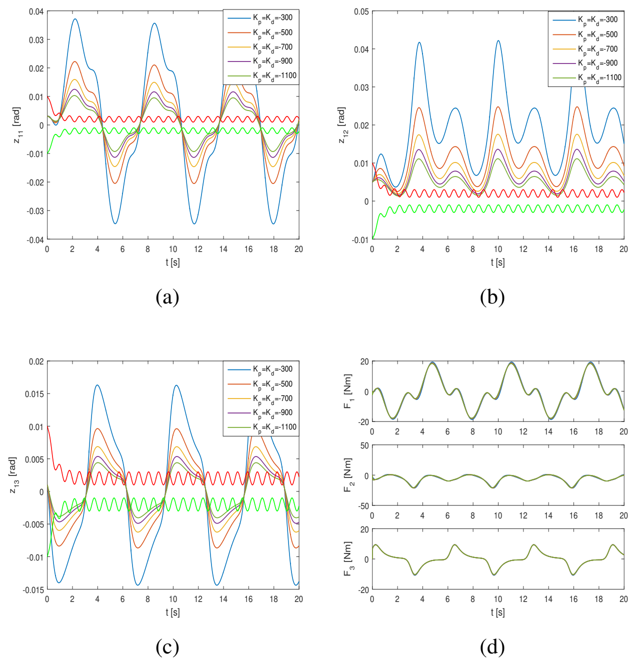

Fig. 6: (a)-(c) Tracking error z_1 with PD control (red: upper constraint bound; green: lower constraint bound; others denote tracking error z_1 based on five different gain parameters). (d) Control input F with PD control.

4.3 Analysis of adaptive FNN control and PD control

By analysing the above simulation results, it is known from Fig. 4(b) that under the action of the proposed control (28), tracking error z_1 still remains in the prescribed time-varying constraint region, while shown in Figs. 6(a)-6(c), after adjusting gain parameters K_p, K_d five times, tracking error z_1 cannot been bounded by the prescribed time-varying constraints. That is because barrier Lyapunov function (17) is positive on condition that tracking error z_1 must remain in the prescribed time-varying constraint region $\pi_{i,2} < z_{1i} < \pi_{i,1}, i = 1, 2, 3$, and tracking error z_1 would decrease with time. PD control stabilizes the closed-loop system without prescribing the shape of tracking error z_1, in other words, PD control only ensures that tracking error z_1 is bounded, and however this bound is difficult to determine. Thus, in dealing with output constraint problems and transient response problems, the proposed control in this paper for relative to PD control has greater advantage. It is known from Fig. 4(b) and Figs. 6(a)-6(c) that after adjusting gain parameters K_p, K_d five times, tracking error z_1 based on PD control is greater than that based on adaptive FNN control. Consequently, the proposed FNN control is more suitable for accurate trajectory tracking.

5 Conclusion

In this paper, an adaptive FNN control scheme is investigated for a marine vessel with full-state constraints and guaranteed transient response. A series of continuous constraint functions are introduced to shape the motion of a marine vessel. Adaptive parameters are designed to compensate the approximation errors of fuzzy neural networks. Via Lyapunov stability theory, it has been proved that the proposed control has the ability to make the system possess a satisfactory transient response performance, and all the states in the closed-loop system are uniformly bounded ultimately without violating the prescribed constraint region. Simulation results have verified the effectiveness of the proposed control. It is known that guaranteed transient response is very important to tracking accuracy, consequently the future work is to design a finite-time convergence control scheme for a marine vessel.

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