Asymmetric Bounded Neural Control for an Uncertain Robot by State Feedback and Output Feedback

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***Abstract*—In this paper, an adaptive neural bounded control scheme is proposed for an n-link rigid robotic manipulator with unknown dynamics. With combination of neural approximation and backstepping technique, an adaptive neural network control policy is developed to guarantee the tracking performance of the robot. Different from the existing results, the bounds of the designed controller are known *a priori*, and they are determined by controller gains, *making them applicable within actuator limitations*. Furthermore, the designed controller is also able to compensate the effect of unknown robotic dynamics. Via Lyapunov stability theory, it can be proved that all the signals are uniformly ultimately bounded (UUB). Simulations are carried out to verify the effectiveness of the proposed scheme.**

***Index Terms*—Neural networks, Asymmetrically bounded inputs, A robotic manipulator, Adaptive control**

I. Introduction

Robots have a wide range of applications in various fields such as prospecting, navigation, aviation and so on [1]–[8]. Control design and stability analysis for a robot are increasingly important and have received considerable attention [9], [10]. A significant topic in the robot field is trajectory tracking [11]. Thus, many research results have been obtained in the past decades [12]–[14]. However, an avoidable challenge for controller design is that there exists model uncertainty due to the fact that robots are highly nonlinear and strongly coupled [15]–[18].

Model-based control has been proved to be effective in practical applications. An inevitable shortcoming for model-based control is that the dynamic information of the controlled system is required to be completely known. For a practical robot, accurate dynamic information is hardly possible to obtain such that model-based controller cannot be directly applied to real implementation. Due to requiring little knowledge [19]–[33], learning control has been widely utilized in control theory and applications to handle system uncertainty. Neural networks serve as a powerful tool to model system uncertainty in a real-time way, which have been widely used for solving the control problems of unknown nonlinear systems [34]–[49]. and are used for complex defects on magnetic flux leakage [50]. In [51], an adaptive neural network control scheme is developed for strict-feedback nonlinear state constrained systems in the presence of input delay and system uncertainty. In [52], neural networks are employed to approximate system uncertainty of multi-input-multi-output nonlinear systems. In [53], an adaptive neural network control method is proposed for unknown nonlinear systems with full-state constraints. In [54], adaptive neural networks are used to deal with the tracking problem for rigid robotic manipulators with uncertainty and output constraints. In most situations, velocity signals are exceedingly difficult or even impossible to measure. Then researchers try to design the state observer to estimate the immeasurable states, and many research results have been carried out [55], [56]. In [57], a state observer is designed to estimate the immeasurable states such that an adaptive neural output feedback control is developed for large-scale stochastic nonlinear systems. In [58], the high-gain observer estimates the velocity signals for an n-link rigid robotic manipulator, and an adaptive output feedback control scheme is developed.

Input saturation exists in most practical robots, which, if not properly coped with, would degrade system performances and even cause instability [59]–[65]. Recently, input saturation has been received considerable attention from analysis and controller design, and furthermore many research results have been derived [66]–[70]. In [66], an auxiliary variable is designed for nonlinear systems with nonsymmetric input saturations and time delays to eliminate the effect of input saturation. In [67], the control problems of multiple strict-feedback nonlinear systems with saturation nonlinearity are discussed, where hyperbolic tangent function $tanh(\cdot)$ is introduced to approximate saturation nonlinearity. In [68], adaptive neural network control is proposed for a class of nonlinear systems with asymmetric saturation actuators. In [69], an adaptive fuzzy control approach is presented for uncertain nonstrict-

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feedback systems with input saturation. In [70], a novel adaptive sliding mode controller is designed for Takagi-Sugeno fuzzy systems with actuator saturation and system uncertainty. An asymmetric saturation situation may be encountered if the actuators partially loss their effectiveness for an uncertain robot, due to motor fault, change of mechanical structure, etc, which drives us to solve the asymmetric saturation constraint problems for an uncertain robot. In [66]–[70], the bounds of the designed controller are considered to be unknown for the controller design, which motivates us to further investigate the adaptive neural network control with asymmetric and known bounds for an n-link rigid robotic manipulator with uncertain dynamics, making the designed controller applicable within actuator limitations.

Motivated by above observations, this paper focuses on the adaptive bounded control for an n-link rigid robotic manipulator with unknown dynamics, where the bounds of the designed controller are asymmetric and known *a prior* and furthermore can be predetermined by changing control gains, *making the designed controller applicable within actuator limitations*. Neural networks are employed to approximate unknown robotic dynamics. A high-gain observer is introduced to estimate the immeasurable states.

Compared with the previous works, the main contributions are summarized as follows:

1) Compared with [66]–[70], a main feature in this paper is that the bounds of the designed controller are asymmetric and known *a priori*, and furthermore they are predetermined by changing control gains.
2) In [66], an additional auxiliary variable is designed to eliminate the effect of input saturation. Compared with [66], we directly adopt hyperbolic tangent function *tanh*$(\cdot)$ to obtain the bounded control. Thus, the structure of the designed controller in this paper may be more simpler to some extent, which is beneficial to controller implementation and real-time control.

The structure of the paper is presented. Section II shows preliminaries and problem formulation. The main results are given in Section III. In Section IV, some simulation examples are provided to demonstrate the effectiveness of the proposed method. Finally, Section V concludes this paper.

Notations 1: Let $\|\bullet\|$ be the Euclidean norm of a vector or a matrix. Let $\mathcal{A}_i$ $(i = 1, \ldots, n)$ denote the ith row and the ith diag element $\mathcal{A}_{ii}$ of the vector $\mathcal{A} \in \mathbb{R}^n$ and the matrix $\mathcal{A} \in \mathbb{R}^{n\times n}$, respectively. The symbol "I" is used to denote an identity matrix with appropriate dimensions.

II. Preliminaries and Problem Formulation

A. Problem Formulation

Consider an n-link rigid robotic manipulator model [71] in joint space as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \mu \tag{1}$$

where $q \in \mathbb{R}^n$, $\dot{q} \in \mathbb{R}^n$, $\ddot{q} \in \mathbb{R}^n$ denote the vector of joint position, velocity and acceleration, $M(q) \in \mathbb{R}^{n\times n}$ denotes the positive definite quality inertia matrix, $C(q,\dot{q}) \in \mathbb{R}^{n\times n}$ denotes the coriolis and centrifugal matrix, $G(q) \in \mathbb{R}^n$ denotes the gravitational forces, $\mu \in \mathbb{R}^n$ denotes the control torque vector and satisfies

$$\mu_{ci}^- \leq \mu_i \leq \mu_{ci}^+ \tag{2}$$

where $\mu_{ci}^+ \in \mathbb{R}^+$, $\mu_{ci}^- \in \mathbb{R}^-$, $i = 1, \ldots, n$, denote the upper and lower bound of μ_i, respectively.

The control objective in this paper is to design an asymmetrically bounded control scheme ensuring: 1) the robot given in (1) can track the reference trajectory x_d with an acceptable accuracy; 2) tracking errors are uniformly ultimately bounded (UUB).

Assumption 1: [72] System matrixes $M(q)$, $C(q,\dot{q})$ and $G(q)$ are unknown, and furthermore $M^{-1}(q)$ exists.

Property 1: [72] $\dot{M}(q) - 2C(q,\dot{q})$ is a skew symmetric matrix. $\forall x \in \mathbb{R}^n$, $x^T(\dot{M}(q) - 2C(q,\dot{q}))x = 0$.

B. Radial Basis Function Neural Networks (RBFNNs)

In the consequent design, unknown nonlinear functions would be approximated by RBFNNs in the following form.

$$h_n(Z) = \hat{\theta}^T\varphi(Z) \tag{3}$$

where $h_n(Z)$ is any nonlinear function, $Z \in \Omega_Z \subset \mathbb{R}^q$ is the input vector, $\hat{\theta} = [\hat{\theta}_1, \ldots, \hat{\theta}_l]^T \in \mathbb{R}^l$ is the weight vector, $l > 1$ is the neural network node number, and $\varphi(Z) = [\varphi_1(Z), \ldots, \varphi_l(Z)]^T$ with $\varphi_i(Z)$ chosen as the Gaussian radial basis function. $\varphi_i(Z)$ is given by

$$\varphi_i(Z) = \exp[\frac{-(Z-\varrho_i)^T(Z-\varrho_i)}{\eta_i^2}] \tag{4}$$

where $\varrho_i = [\varrho_{i1}, \ldots, \varrho_{iq}]^T$ is the center of the receptive field and η_i is the width of the Gaussian radial basis function, $i = 1, \ldots, n$.

Lemma 1: [73] For given accuracy $\epsilon > 0$ with sufficiently large node number l, neural networks (3) can approximate any continuous nonlinear function $h(Z)$ defined in the compact set $\Omega \subset \mathbb{R}^q$ such that

$$h(Z) = \theta^T\varphi(Z) + \epsilon(Z), \quad \forall Z \in \Omega \subset \mathbb{R}^q \tag{5}$$

where θ is the optimal weight defined as

$$\theta := \arg\min_{\hat{\theta}\subset\mathbb{R}^l}\left\{\sup_{Z\in\Omega}|h(Z) - \hat{\theta}^T\varphi(Z)|\right\}, \tag{6}$$

and $\epsilon(Z)$ is the approximation error satisfying $\|\epsilon(Z)\| \leq \bar{\epsilon}$ with $\bar{\epsilon}$ being positive constants.

Lemma 2: [73] Given that the Gaussian radial basis function with $\hat{Z} = Z - \bar{\gamma}\nu$ being the input vector, where ν is a bounded vector and $\bar{\gamma}$ is a positive constant, then we have

$$\varphi_i(\hat{Z}) = \exp[\frac{-(\hat{Z}-\varrho_i)^T(\hat{Z}-\varrho_i)}{\eta_i^2}], \quad i = 1, \ldots, l \tag{7}$$

$$\varphi(\hat{Z}) = \varphi(Z) + \bar{\gamma}\varphi \tag{8}$$

$$\|\varphi(Z)\|^2 \leq l \tag{9}$$

where φ is a bounded function vector.

C. Useful Properties, Definitions and Lemmas

Property 2: [72] $\mathcal{A} \in \mathbb{R}^{n\times n}$ is a symmetric positive definite matrix. $\lambda_{\min}(\mathcal{A})$ and $\lambda_{\max}(\mathcal{A})$ are the minimum and maximum eigenvalues of $\mathcal{A}$. For $\forall x \in \mathbb{R}^n$, there is $\lambda_{\min}(\mathcal{A})||x||^2 \leq x^T\mathcal{A}x \leq \lambda_{\max}(\mathcal{A})||x||^2$.

η_i, $i = 1, \ldots, n$,

Definition 1: Define the diagonal matrix $\mathrm{Tanh}^2(.) \in \mathbb{R}^{n\times n}$ as follows:

$$\mathrm{Tanh}^2(\eta) = \mathrm{diag}[\tanh^2(\eta_1), \ldots, \tanh^2(\eta_n)] \tag{10}$$

where $\eta = [\eta_1, \ldots, \eta_n]^T \in \mathbb{R}^n$.

Lemma 3: Assume that $f(\mu)$ is an asymmetric saturation function represented as

$$f(\mu) = \begin{cases} \mu_c^+ & \text{if } \mu_c^+ < \mu \\ \mu & \text{if } \mu_c^- \leq \mu \leq \mu_c^+ \\ \mu_c^- & \text{Otherwise} \end{cases} \tag{11}$$

where μ_c^+ and μ_c^- are the upper and lower bound of μ, respectively. When $\mu = \mu_c^+$ or $\mu = \mu_c^-$, there is a sharp corner. Then a novel smooth function is introduced to approximate this saturation function in the following form.

$$f(\mu) = \delta\mu_c^+ \tanh(\frac{\mu}{\mu_c^+}) + (1-\delta)\mu_c^- \tanh(\frac{\mu}{\mu_c^-}) + p(\mu) \tag{12}$$

where δ denotes a switching function defined as [74]

$$\delta = \begin{cases} 1 & \text{if } \mu \geq 0 \\ 0 & \text{Otherwise} \end{cases} \tag{13}$$

and $p(\mu)$ denotes a bounded function. Then we present a proof showing that $p(\mu)$ is bounded.

Proof: Two cases are considered as follows:

- Case one: $\mu > \mu_c^+$. (12) is rewritten as $f(\mu) = \mu_c^+ \tanh(\frac{\mu}{\mu_c^+}) + p(\mu)$. With combination of (11), it follows that $|p(\mu)| = |\mu_c^+(1 - \tanh(\frac{\mu}{\mu_c^+}))| \leq |\mu_c^+|$, which illustrates that $p(\mu)$ is bounded for the case $\mu > \mu_c^+$. Similar proof can also be presented for the case $\mu_c^- > \mu$.
- Case two: $0 \leq \mu \leq \mu_c^+$. (12) is rewritten as $f(\mu) = \mu_c^+ \tanh(\frac{\mu}{\mu_c^+}) + p(\mu)$. With combination of (11), it follows that $p(\mu) = \mu - \mu_c^+ \tanh(\frac{\mu}{\mu_c^+}) \leq \mu_c^+(1 - \tanh(\frac{\mu}{\mu_c^+}))$, similarly, implying that $p(\mu)$ is bounded when $0 \leq \mu \leq \mu_c^+$. Similar proof can also be presented for the case $\mu_c^- \leq \mu < 0$.

III. Control Design

For the convenience of controller design, before controller design, we define $x_1 = q$ and $x_2 = \dot{q}$, and then (1) can be rewritten as

$$\dot{x}_1 = x_2 \tag{14}$$

$$\dot{x}_2 = M^{-1}(\mu - G - Cx_2) \tag{15}$$

where $x_1 = [x_{11}, \ldots, x_{1n}]^T$, $x_2 = [x_{21}, \ldots, x_{2n}]^T$. In the subsequent design, M, C and G denote $M(x_1)$, $C(x_1, x_2)$ and $G(x_1)$, respectively.

A. Model-based Control Design

Tracking errors are defined as

$$z_1 = x_1 - x_d \tag{16}$$

$$z_2 = x_2 - \alpha \tag{17}$$

where α is defined as

$$\alpha = -A + \dot{x}_d \tag{18}$$

where $A = [\frac{k_1 \ln\cosh(z_{11})}{\tanh(z_{11}}, \ldots, \frac{k_n \ln\cosh(z_{1n})}{\tanh(z_{1n})}]^T \in \mathbb{R}^n$, and $K = \mathrm{diag}[k_1, \ldots, k_n] \in \mathbb{R}^{n\times n}$ is a positive definite matrix. Then error dynamics is calculated as

$$\dot{z}_1 = z_2 - A \tag{19}$$

$$\dot{z}_2 = M^{-1}(\mu - G - Cx_2) - \dot{\alpha} \tag{20}$$

Choose a positive Lyapunov function candidate as

$$V_1 = \sum_{i=1}^{n} \ln(\cosh(z_{1i})) + \frac{1}{2} z_2^T M z_2 \tag{21}$$

Substituting (19) and (20) into the time derivative of (21), we get

$$\begin{aligned}\dot{V}_1 = &- \sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) + \sum_{i=1}^{n} z_{2i} \tanh(z_{1i}) \\ &+ z_2^T(\mu - G - C\alpha - M\dot{\alpha})\end{aligned} \tag{22}$$

Then, model-based control μ is designed as

$$\mu = -\tanh(z_1) - K_1 \tanh(z_2) + B\tanh(B^{-1}\psi) \tag{23}$$

where $\mu = [\mu_1, \ldots, \mu_n]^T \in \mathbb{R}^n$, $K_1 = \mathrm{diag}[k_{11}, \ldots, k_{1n}] \in \mathbb{R}^{n\times n}$ is a positive definite matrix, and $B = \mathrm{diag}[\delta_i\mu_i^+ + (1-\delta_i)\mu_i^-] \in \mathbb{R}^{n\times n}$ with μ_i^- being negative constants and μ_i^+ being positive constants. It should be emphasized that μ_i^- and μ_i^+ are also considered as adjustable control gains. Auxiliary variable ψ is defined as

$$\begin{aligned}\psi_i = &\delta_i\mu_i^+ \mathrm{arctanh}\left(\frac{(G + C\alpha + M\dot{\alpha})_i}{\mu_i^+}\right) \\ &+ (1-\delta_i)\mu_i^- \mathrm{arctanh}\left(\frac{(G + C\alpha + M\dot{\alpha})_i}{\mu_i^-}\right)\end{aligned} \tag{24}$$

where $\mathrm{arctanh}(\cdot)$ denotes the inverse function of $\tanh(\cdot)$, and $\psi = [\psi_1, \ldots, \psi_n]^T \in \mathbb{R}^n$. We assume that initial values satisfy $\mu_i^- < (G + C\alpha + M\dot{\alpha})_i(0) < \mu_i^+$. δ_i is a switching function defined as

$$\delta_i = \begin{cases} 1 & \text{if } (G + C\alpha + M\dot{\alpha})_i > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{25}$$

Substituting (23) into (22), we get

$$\begin{aligned}\dot{V}_1 = &- \sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - z_2^T K_1 \tanh(z_2) \\ &+ z_2^T(B\tanh(B^{-1}\psi) - G - C\alpha - M\dot{\alpha})\end{aligned} \tag{26}$$

Define $f(\mu) = G + C\alpha + M\dot{\alpha}$, and by ultilizing Lemma 3, we have $f(\mu) = B\tanh(B^{-1}\psi) + p(\mu)$, where $p(\mu)$ denotes the approximation error, and furthermore it is assumed that $p(\mu)$ is upper bounded, i.e., $\|p(\mu)\| \leq \bar{p}$ with $\bar{p}$ being unknown positive constants. Thus we have $z_2^T(B\tanh(B^{-1}\psi) - G - C\alpha - M\dot{\alpha}) = -z_2^T p(\mu) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{p}^2$. According to Taylor expansion, we know

$$\tanh(z_2) = z_2 + o(z_2), \quad \|z_2\| < \frac{\pi}{2} \tag{27}$$

where $o(z_2) = -\frac{1}{3}z_2^3 + \frac{2}{15}z_2^5 - \frac{17}{315}z_2^7 + \cdots$, and in the interval $\|z_2\| < \frac{\pi}{2}$, $o(z_2)$ is bounded, i.e., $\|o(z_2)\| \le \bar{o}$ with $\bar{o}$ being a positive constant. With aid of Young's inequality, thus (26) becomes

$$\begin{aligned}\dot{V}_1 =& -\sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - z_2^T K_1 z_2 - z_2^T K_1 o(z_2) \\ &+ \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{p}^2 \\ \le& -\kappa_1 V_1 + C_1 \end{aligned} \tag{28}$$

where $\kappa_1 = \min\left\{\min_{i=1,\ldots,n} k_i, \frac{\lambda_{\min}(K_1 - I)}{\lambda_{\max}(M)}\right\}$, $C_1 = \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}^2 + \frac{1}{2}\bar{p}^2$. To ensure $\kappa_1 > 0$, controller parameters should satisfy $\min_{i=1,\ldots,n} k_i > 0$ and $\lambda_{\min}(K_1 - I) > 0$. Then the following theorem is obtained.

Theorem 1: For robotic system (1), by designing model-based control input (23), the controller can ensure that all the error signals are UUB. Furthermore, z_1 eventually converges to the compact set defined as $\Omega_{z_1} := \left\{z_1 \in \mathbb{R}^n \big| |z_{1i}| \le \sqrt{2e^{H_1}}, i = 1, \ldots, n\right\}$, and z_2 eventually converges to the compact set defined as $\Omega_{z_2} := \left\{z_2 \in \mathbb{R}^n \big| ||z_2|| \le \sqrt{\frac{2H_1}{\lambda_{\min}(M)}}\right\}$, where $H_1 = V_1(0) + \frac{C_1}{\kappa_1}$.

Proof: See Appendix

Remark 1: If $\delta_i = 1$, (23) can be rewritten as $\mu_i = -\tanh(z_{1i}) - k_{1i}\tanh(z_{2i}) + \mu_i^+ \tanh(\frac{\psi_i}{\mu_i^+})$, $i = 1, \ldots, n$, and by the utilization of the property of the continuous function $\tanh(\cdot)$, we know that μ_i is upper bounded, i.e., $\mu_i \le 1 + k_{1i} + \mu_i^+$. If $\delta_i = 0$, (23) can reduce to $\mu_i = -\tanh(z_{1i}) - k_{1i}\tanh(z_{2i}) + \mu_i^- \tanh(\frac{\psi_i}{\mu_i^-})$, $i = 1, \ldots, n$, and we further know that μ_i is also lower bounded, i.e., $\mu_i \ge -(1 + k_{1i} + \mu_i^-)$. Then, defining $\mu_{ci}^+ = 1 + k_{1i} + \mu_i^+$ and $\mu_{ci}^- = -(1 + k_{1i} + \mu_i^-)$ implies $\mu_{ci}^- \le \mu_i \le \mu_{ci}^+, i = 1, \ldots, n$. It should be noted that k_{1i}, μ_i^+ and μ_i^-, $i = 1, \ldots, n$ can also be considered as controller gains, which, if necessary, may also change for both satisfactory tracking performances and suitable bounds of controllers, making the controller applicable within actuator limitations.

B. State-Feedback-Based Adaptive Neural Control Design

Assume that M, C and G are unknown such that model-based control (23) is unavailable in practice. Furthermore, auxiliary variable ψ given in (24) is also unknown. Then neural networks are employed to approximate ψ in the following form.

$$\theta^T \varphi(Z) = \psi + \epsilon(Z) \tag{29}$$

where θ is the desired weight vector, $Z = [x_1^T, x_2^T, z_1^T, z_2^T]^T \in \mathbb{R}^{4n}$ is the input of RBFNNs, and $\epsilon(Z)$ is the approximation error satisfying $\|\epsilon(Z)\| \le \bar{\epsilon}$ with $\bar{\epsilon}$ being a positive constant. Then an adaptive neural network controller is designed as

$$\mu = -\tanh(z_1) - K_1\tanh(z_2) + B\tanh(B^{-1}\hat{\psi}) \tag{30}$$

$$\hat{\psi} = \hat{\theta}^T \varphi(Z) \tag{31}$$

$$\dot{\hat{\theta}}_i = -\Gamma_i(\varphi(Z)z_{2i} + \varsigma\hat{\theta}_i), \quad i = 1, \ldots, n \tag{32}$$

where $K_1 = \mathrm{diag}[k_{11}, \ldots, k_{1n}] \in \mathbb{R}^{n\times n}$ is a positive definite matrix, $B = \mathrm{diag}[\delta_i\mu_i^+ + (1-\delta_i)\mu_i^-] \in \mathbb{R}^{n\times n}$ with δ_i defined as

$$\delta_i = \begin{cases} 1 & \text{if } \hat{\theta}_i^T\varphi(Z) \ge \ell_i \\ 0 & \text{Otherwise,} \end{cases} \tag{33}$$

$\ell_i \triangleq \tilde{\theta}_i^T\varphi(Z) + \epsilon_i(Z)$, $(\hat{\bullet})$ denotes the estimation of $(\bullet)$ satisfying $(\tilde{\bullet}) = (\hat{\bullet}) - (\bullet)$, Γ_i is a symmetric positive definite matrix, and ς is a small constant which improves the robustness.

Remark 2: Note that switching function δ_i given in (25) is based on an assumption that M, C and G are all known. However, in this section M, C and G are assumed to be unknown, which causes switching function δ_i given in (25) to be ineffective. Therefore switching function δ_i need redesigned again. Due to the fact that $\theta^T\varphi(Z) = \hat{\theta}^T\varphi(Z) - \tilde{\theta}^T\varphi(Z)$, (29) is rewritten as $\psi = \hat{\theta}^T\varphi(Z) - \tilde{\theta}^T\varphi(Z) - \epsilon(Z)$. Let us recall switching function δ_i given in (25) and consider the fact that $\mathrm{arctanh}(.)$ is an odd function, and we know: 1) when $(G + C\alpha + M\dot{\alpha})_i \ge 0$, it follows that $\psi_i \ge 0$ and $\hat{\theta}_i^T\varphi(Z) \ge \tilde{\theta}_i^T\varphi(Z) + \epsilon_i(Z)$; 2) when $(G + C\alpha + M\dot{\alpha})_i < 0$, it follows that $\psi_i < 0$ and $\hat{\theta}_i^T\varphi(Z) < \tilde{\theta}_i^T\varphi(Z) + \epsilon_i(Z)$. By defining $\ell_i = \tilde{\theta}_i^T\varphi(Z) + \epsilon_i(Z)$, one can obtain the switch function δ_i given in (33), $i = 1, \ldots, n$.

Similar to analysis in Remark 1, we can conclude that $\mu_i, i = 1, \ldots, n$ given in (30) are bounded, i.e., $\mu_{ci}^- \le \mu_i \le \mu_{ci}^+, i = 1, \ldots, n$, are guaranteed. A Lyapunov function candidate is chosen as

$$V_2 = \sum_{i=1}^{n} \ln(\cosh(z_{1i})) + \frac{1}{2}z_2^T M z_2 + \frac{1}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\Gamma_i^{-1}\tilde{\theta}_i \tag{34}$$

Substituting (19) and (20) into the time derivative of (34), we get

$$\begin{aligned}\dot{V}_2 =& -\sum_{i=1}^{n} k_i\ln(\cosh(z_{1i})) + \sum_{i=1}^{n} z_{2i}\tanh(z_{1i}) \\ &+ z_2^T(\mu - G - C\alpha - M\dot{\alpha}) + \sum_{i=1}^{n}\tilde{\theta}_i^T\Gamma_i^{-1}\dot{\hat{\theta}}_i \end{aligned} \tag{35}$$

Substituting (30) and (32) into (35), we further get

$$\begin{aligned}\dot{V}_2 =& -\sum_{i=1}^{n} k_i\ln(\cosh(z_{1i})) - \sum_{i=1}^{n}\tilde{\theta}_i^T(\varphi(Z)z_{2i} + \varsigma\hat{\theta}_i) \\ &- z_2^T K_1\tanh(z_2) + z_2^T(B\tanh(B^{-1}\hat{\psi}) \\ &- G - C\alpha - M\dot{\alpha}) \end{aligned} \tag{36}$$

Define $f(\mu) = G + C\alpha + M\dot{\alpha}$, and by utilizing Lemma 3, we have $f(\mu) = B\tanh(B^{-1}\psi) + p(\mu)$, where $p(\mu)$ denotes the approximation error, and furthermore it is assumed that $p(\mu)$ is upper bounded, i.e., $\|p(\mu)\| \le \bar{p}$ with $\bar{p}$ being unknown positive constants. Then we know that $z_2^T(B\tanh(B^{-1}\hat{\psi}) -$

$G - C\alpha - M\dot{\alpha})$ becomes $z_2^T B(\tanh(B^{-1}\hat{\psi}) - \tanh(B^{-1}\psi)) - z_2^T p(\mu)$. According to mean value theorem, we have

$$\begin{aligned}&\tanh(B_i^{-1}\hat{\psi}_i) - \tanh(B_i^{-1}\psi_i)\\&\qquad = (1-\tanh^2(\eta_i))(B_i^{-1}(\hat{\psi}_i - \psi_i))\end{aligned} \tag{37}$$

where $\eta_i \in (B_i^{-1}\hat{\psi}_i, B_i^{-1}\psi_i)$ or $\eta_i \in (B_i^{-1}\psi_i, B_i^{-1}\hat{\psi}_i)$ and $B^{-1} = \mathrm{diag}[B_1^{-1}, \ldots, B_n^{-1}]$, $i = 1, \ldots, n$. Using (29) and (31), we have $\tanh(B_i^{-1}\hat{\psi}_i) - \tanh(B_i^{-1}\psi_i) = (1 - \tanh^2(\eta_i))B_i^{-1}(\tilde{\theta}_i^T\varphi(Z) + \epsilon_i(Z))$, $i = 1, \ldots, n$. Therefore, (36) becomes

$$\begin{aligned}\dot{V}_2 =& -\sum_{i=1}^n k_i \ln(\cosh(z_{1i})) - \sum_{i=1}^n \tilde{\theta}_i^T(\varphi(Z)z_{2i} + \varsigma\hat{\theta}_i)\\&- z_2^T K_1 \tanh(z_2) + z_2^T(I - \mathrm{Tanh}^2(\eta))\\&\times(\tilde{\theta}^T\varphi(Z) + \epsilon(Z)) - z_2^T p(\mu)\end{aligned} \tag{38}$$

Note that $\sum_{i=1}^n \tilde{\theta}_i^T\varphi(Z)z_{2i} = z_2^T\tilde{\theta}^T\varphi(Z)$ and consider (27), we further have

$$\begin{aligned}\dot{V}_2 =& -\sum_{i=1}^n k_i \ln(\cosh(z_{1i})) - \sum_{i=1}^n \tilde{\theta}_i^T\varsigma\hat{\theta}_i - z_2^T K_1 z_2\\&- z_2^T K_1 o(z_2) - z_2^T\mathrm{Tanh}^2(\eta)(\tilde{\theta}^T\varphi(Z) + \epsilon(Z))\\&+ z_2^T\epsilon(Z) - z_2^T p(\mu)\end{aligned} \tag{39}$$

In terms of Young's inequality, we obtain $z_2^T K_1 o(z_2) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}^2$, $-\sum_{i=1}^n \tilde{\theta}_i^T\varsigma\hat{\theta}_i \le -\frac{\varsigma}{2}\sum_{i=1}^n \tilde{\theta}_i^T\tilde{\theta}_i + \frac{\varsigma}{2}\sum_{i=1}^n \theta_i^T\theta_i$, $-z_2^T\mathrm{Tanh}^2(\eta)\tilde{\theta}^T\varphi(Z) \le \frac{\varrho_1^2}{2}z_2^T z_2 + \frac{l^2}{2\varrho_1^2}\sum_{i=1}^n \tilde{\theta}_i^T\tilde{\theta}_i$, $-z_2^T\mathrm{Tanh}^2(\eta)\epsilon(Z) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{\epsilon}^2$, $z_2^T\epsilon(Z) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{\epsilon}^2$, and $-z_2^T p(\mu) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{p}^2$, where ϱ_1 is an adjustable parameter. Thus, we have

$$\begin{aligned}\dot{V}_2 \le& -\sum_{i=1}^n k_i \ln(\cosh(z_{1i})) - z_2^T\left(K_1 - (\frac{4+\varrho_1^2}{2})I\right)z_2\\&- \frac{1}{2}\left(\varsigma - \frac{l^2}{\varrho_1^2}\right)\sum_{i=1}^n \tilde{\theta}_i^T\tilde{\theta}_i + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}^2\\&+ \frac{\varsigma}{2}\sum_{i=1}^n \theta_i^T\theta_i + \bar{\epsilon}^2 + \frac{1}{2}\bar{p}^2\\\le& -\kappa_2 V_2 + C_2\end{aligned} \tag{40}$$

where

$$\begin{aligned}\kappa_2 =& \min\Bigg\{\min_{i=1,\ldots,n} k_i, \min_{i=1,\ldots,n}\left(\varsigma - \frac{l^2}{\varrho_1^2}\right)\frac{1}{\lambda_{\max}(\Gamma_i^{-1})},\\&\lambda_{\min}\left(2K_1 - (4+\varrho_1^2)I\right)\frac{1}{\lambda_{\max}(M)}\Bigg\}\\C_2 =& \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}^2 + \frac{\varsigma}{2}\sum_{i=1}^n \theta_i^T\theta_i + \bar{\epsilon}^2 + \frac{1}{2}\bar{p}^2\end{aligned}$$

To guarantee $\kappa_2 > 0$, controller parameters should be chosen to satisfy: $\min_{i=1,\ldots,n} k_i > 0$, $\min_{i=1,\ldots,n}\left(\varsigma - \frac{l^2}{\varrho_1^2}\right) > 0$ and $\lambda_{\min}\left(2K_1 - (4+\varrho_1^2)I\right) > 0$. Then the following theorem is obtained.

Theorem 2: For robotic system (1), by designing adaptive neural network controller (30) with adaptive law (32), the controller can ensure that all the error signals are UUB. Furthermore, z_1 eventually converges to the compact set defined as $\Omega_{z_1} := \left\{z_1 \in \mathbb{R}^n \middle| |z_{1i}| \le \sqrt{2e^{H_2}}, i = 1, \ldots, n\right\}$, and z_2 eventually converges to the compact set defined as $\Omega_{z_2} := \left\{z_2 \in \mathbb{R}^n \middle| ||z_2|| \le \sqrt{\frac{2H_2}{\lambda_{\min(M)}}}\right\}$, where $H_2 = V_2(0) + \frac{C_2}{\kappa_2}$.

Proof: The proof is similar to that of Theorem 1, so it will not be discussed in details.

C. Output-Feedback-Based Adaptive Neural Control Design

Assume that velocity signal x_2 is immeasurable. We will introduce a high-gain observer to estimate x_2. x_2 is estimated by $\hat{x}_2 = \frac{\pi_2}{\rho}$. Estimate error is defined as $\tilde{z}_2 = \frac{\pi_2}{\rho} - x_2$ and is said to be bounded [73], i.e., $\|\tilde{z}_2\| \le \bar{z}$ with $\bar{z}$ being a positive constant. Dynamics of π_2 is given as

$$\rho\dot{\pi}_1 = \pi_2, \tag{41}$$

$$\rho\dot{\pi}_2 = -\lambda_1\pi_2 - \pi_2 + x_1 \tag{42}$$

where λ_1 is a constant satisfying that $\lambda_1 s + 1$is Hurwitz, and ρ is a number. An adaptive neural controller is designed as

$$\mu = -\tanh(z_1) - K_1\tanh(\hat{z}_2) + B\tanh(B^{-1}\hat{\psi}) \tag{43}$$

$$\hat{\psi} = \hat{\theta}^T\varphi(\hat{Z}) \tag{44}$$

$$\dot{\hat{\theta}}_i = -\Gamma_i(\varphi(\hat{Z})\hat{z}_{2i} + \varsigma\hat{\theta}_i), \quad i = 1, \ldots, n \tag{45}$$

where $K_1 = \mathrm{diag}[k_{11}, \ldots, k_{1n}] \in \mathbb{R}^{n\times n}$ is a positive definite matrix, $\hat{Z} = [x_1^T, \hat{x}_2^T, z_1^T, \hat{z}_2^T]^T \in \mathbb{R}^{4n}$, $\hat{z}_2 = \frac{\pi_2}{\rho} - \alpha$, $B = \mathrm{diag}[\delta_i\mu_i^+ + (1-\delta_i)\mu_i^-] \in \mathbb{R}^{n\times n}$ with δ_i defined as

$$\delta_i = \begin{cases}1 & \text{if } \hat{\theta}_i^T\varphi(\hat{Z}) \ge \beta_i\\0 & \text{Otherwise,}\end{cases} \tag{46}$$

and $\beta_i = \hat{\theta}_i^T\bar{\gamma}\varphi + \ell_i$ with ℓ_i defined in (33), $i = 1, \ldots, n$.

Remark 3: A difference from switching function δ_i in (33) is that velocity signal x_2 in this section is estimated by a high-gain observer. Thus the switching function δ_i in (33) should be redesigned. According to (8), we can obtain $\hat{\theta}_i^T\varphi(Z) = \hat{\theta}_i^T\varphi(\hat{Z}) - \hat{\theta}_i^T\bar{\gamma}\varphi$. Consider (8) and (33), we know that if $\delta_i = 1$, it follows that $\hat{\theta}_i^T\varphi(Z) = \hat{\theta}_i^T\varphi(\hat{Z}) - \hat{\theta}_i^T\bar{\gamma}\varphi \ge \ell_i$ and $\hat{\theta}_i^T\varphi(\hat{Z}) \ge \hat{\theta}_i^T\bar{\gamma}\varphi + \ell_i$, and if $\delta_i = 0$, it follows that $\hat{\theta}_i^T\varphi(Z) = \hat{\theta}_i^T\varphi(\hat{Z}) - \hat{\theta}_i^T\bar{\gamma}\varphi < \ell_i$ and $\hat{\theta}_i^T\varphi(\hat{Z}) < \hat{\theta}_i^T\bar{\gamma}\varphi + \ell_i$. Defining $\beta_i = \hat{\theta}_i^T\bar{\gamma}\varphi + \ell_i$, we can obtain the switching function δ_i in (46), $i = 1, \ldots, n$.

Similar to analysis in Remark 1, we can conclude that $\mu_i, i = 1, \ldots, n$ given in (43) are bounded, i.e., $\mu_{ci}^- \le \mu_i \le \mu_{ci}^+, i = 1, \ldots, n$, are guaranteed. A Lyapunov function candidate is chosen as

$$V_3 = \sum_{i=1}^n \ln(\cosh(z_{1i})) + \frac{1}{2}z_2^T M z_2 + \frac{1}{2}\sum_{i=1}^n \tilde{\theta}_i^T\Gamma_i^{-1}\tilde{\theta}_i \tag{47}$$

Substituting (43)-(45) into the time derivative of (47), we further have

$$\dot{V}_3 = -\sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - \sum_{i=1}^{n} \tilde{\theta}_i^T(\varphi(\hat{Z})\hat{z}_{2i} + \varsigma\hat{\theta}_i) - z_2^T K_1 \tanh(\hat{z}_2) + z_2^T(B\tanh(B^{-1}\hat{\psi}) - B\tanh(B^{-1}\psi) - p(\mu)) \quad (48)$$

Similar with calculation in III-B, $B\tanh(B^{-1}\hat{\psi}) - B\tanh(B^{-1}\psi)$ can be simplified as $B_i\tanh(B_i^{-1}\hat{\psi}_i) - B_i\tanh(B_i^{-1}\psi_i) = (1-\tanh^2(\eta_i))(\hat{\psi}_i - \psi_i)$, where $\eta_i \in (B_i^{-1}\hat{\psi}_i, B_i^{-1}\psi_i)$ or $\eta_i \in (B_i^{-1}\psi_i, B_i^{-1}\hat{\psi}_i)$. With combination of (8), (29) and (44), we have $\hat{\psi}_i - \psi_i = \tilde{\theta}_i^T\varphi(Z) + \tilde{\theta}_i^T\bar{\gamma}\varphi + \theta_i^T\bar{\gamma}\varphi + \epsilon_i(Z)$, $i = 1, \ldots, n$. According to Taylor expansion, we know

$$\tanh(\hat{z}_2) = \hat{z}_2 + o(\hat{z}_2), \quad \|\hat{z}_2\| < \frac{\pi}{2} \quad (49)$$

where $o(\hat{z}_2) = -\frac{1}{3}\hat{z}_2^3 + \frac{2}{15}\hat{z}_2^5 - \frac{17}{315}\hat{z}_2^7 + \cdots$, and in the interval $\|\hat{z}_2\| < \frac{\pi}{2}$, $o(\hat{z}_2)$ is bounded, i.e., $\|o(\hat{z}_2)\| \le \bar{o}_c$ with $\bar{o}_c$ being a positive constant. Thus, (48) becomes

$$\dot{V}_3 = -\sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - \sum_{i=1}^{n} \tilde{\theta}_i^T(\varphi(\hat{Z})\hat{z}_{2i} + \varsigma\hat{\theta}_i) - z_2^T K_1 \hat{z}_2 - z_2^T K_1 o(\hat{z}_2) + z_2^T(I - \mathrm{Tanh}^2(\eta)) \times (\tilde{\theta}^T\varphi(Z) + \tilde{\theta}^T\bar{\gamma}\varphi + \theta^T\bar{\gamma}\varphi + \epsilon(Z)) - z_2^T p(\mu) \quad (50)$$

Note that

$$\tilde{z}_2 = \frac{\pi_2}{\rho} - x_2 = \hat{x}_2 - x_2 = (\hat{x}_2 - \alpha) - (x_2 - \alpha) = \hat{z}_2 - z_2 \quad (51)$$

Thus, we have $-\sum_{i=1}^{n}\tilde{\theta}_i^T\varphi(\hat{Z})\hat{z}_{2i} + z_2^T\tilde{\theta}^T\varphi(Z) = -\sum_{i=1}^{n}\tilde{\theta}_i^T(\varphi(\hat{Z})\hat{z}_{2i} - \varphi(Z)z_{2i})$. Since $\varphi(\hat{Z}) = \varphi(Z) + \bar{\gamma}\varphi$, we have

$$\begin{aligned} &-\sum_{i=1}^{n}\tilde{\theta}_i^T\varphi(\hat{Z})\hat{z}_{2i} + z_2^T\tilde{\theta}^T\varphi(Z) \\ &= -\sum_{i=1}^{n}\tilde{\theta}_i^T(\varphi(Z)\hat{z}_{2i} + \bar{\gamma}\varphi\hat{z}_{2i} - \varphi(Z)z_{2i}) \\ &= -\sum_{i=1}^{n}\tilde{\theta}_i^T(\varphi(Z)\tilde{z}_{2i} + \bar{\gamma}\varphi z_{2i} + \bar{\gamma}\varphi\tilde{z}_{2i}) \end{aligned} \quad (52)$$

Thus, we have

$$\dot{V}_3 = -\sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - z_2^T K_1 z_2 - \sum_{i=1}^{n}\tilde{\theta}_i^T\varsigma\hat{\theta}_i - z_2^T K_1\tilde{z}_2 - z_2^T K_1 o(\hat{z}_2) - \sum_{i=1}^{n}\tilde{\theta}_i^T(\varphi(Z)\tilde{z}_{2i} + \bar{\gamma}\varphi z_{2i} + \bar{\gamma}\varphi\tilde{z}_{2i}) + 2|z_2^T(\tilde{\theta}^T\bar{\gamma}\varphi + \theta^T\bar{\gamma}\varphi + \epsilon(Z))| + |z_2^T\tilde{\theta}^T\varphi(Z)| - z_2^T p(\mu) \quad (53)$$

In terms of Young's inequality, we have $-z_2^T p(\mu) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{p}^2$, $-\sum_{i=1}^{n}\tilde{\theta}_i^T\varsigma\hat{\theta}_i \le -\frac{\varsigma}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{\varsigma}{2}\sum_{i=1}^{n}\theta_i^T\theta_i$, $-z_2^T K_1\tilde{z}_2 \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{z}^2$, $z_2^T K_1 o(\hat{z}_2) \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}_c^2$, $-\sum_{i=1}^{n}\tilde{\theta}_i^T\varphi(Z)\tilde{z}_{2i} \le \frac{\varrho_2^2}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{1}{2\varrho_2^2}l^2\bar{z}^2$, $-\sum_{i=1}^{n}\tilde{\theta}_i^T\bar{\gamma}\varphi z_{2i} \le \frac{\varrho_3^2}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{\bar{\gamma}^2\|\varphi\|^2}{2\varrho_3^2}z_2^T z_2$, $-\sum_{i=1}^{n}\tilde{\theta}_i^T\bar{\gamma}\varphi\tilde{z}_{2i} \le \frac{\varrho_4^2}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{\bar{\gamma}^2\|\varphi\|^2}{2\varrho_4^2}\bar{z}^2$, $|z_2^T\tilde{\theta}^T\varphi(Z)| \le \frac{\varrho_5^2}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{l^2}{2\varrho_5^2}z_2^T z_2$, $|z_2^T\tilde{\theta}^T\bar{\gamma}\varphi| \le \frac{\varrho_3^2}{2}\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i + \frac{\bar{\gamma}^2\|\varphi\|^2}{2\varrho_3^2}z_2^T z_2$, $|z_2^T\theta^T\bar{\gamma}\varphi| \le \frac{\varrho_3^2}{2}\sum_{i=1}^{n}\theta_i^T\theta_i + \frac{\bar{\gamma}^2\|\varphi\|^2}{2\varrho_3^2}z_2^T z_2$, and $|z_2^T\epsilon(Z)| \le \frac{1}{2}z_2^T z_2 + \frac{1}{2}\bar{\epsilon}^2$. Therefore, we have

$$\begin{aligned} \dot{V}_3 \le& -\sum_{i=1}^{n} k_i \ln(\cosh(z_{1i})) - z_2^T\bigg(K_1 - \frac{1}{2}(5 + \bar{\gamma}^2\|\varphi\|^2 \\ &\times \frac{5}{\varrho_3^2} + \frac{l^2}{\varrho_5^2})I\bigg)z_2 - \frac{1}{2}(\varsigma - \varrho_2^2 - 3\varrho_3^2 - \varrho_4^2 - \varrho_5^2)\sum_{i=1}^{n}\tilde{\theta}_i^T\tilde{\theta}_i \\ &+ \frac{1}{2}(\varsigma + 2\varrho_3^2)\sum_{i=1}^{n}\theta_i^T\theta_i + \frac{1}{2}\bigg(\frac{l^2}{\varrho_2^2} + \frac{\bar{\gamma}^2\|\varphi\|^2}{\varrho_4^2} \\ &+ \lambda_{\max}(K_1^T K_1)\bigg)\bar{z}^2 + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}_c^2 + \bar{\epsilon}^2 + \frac{1}{2}\bar{p}^2 \\ \le& -\kappa_3 V_3 + C_3 \end{aligned} \quad (54)$$

where

$$\kappa_3 = \min\Bigg\{\min_{i=1,\ldots,n} k_i, \frac{\lambda_{\min}\Big(2K_1 - (5 + \frac{5\bar{\gamma}^2\|\varphi\|^2}{\varrho_3^2} + \frac{l^2}{\varrho_5^2})I\Big)}{\lambda_{\max}(M)} \min_{i=1,\ldots,n}\Bigg(\frac{(\varsigma - \varrho_2^2 - 3\varrho_3^2 - \varrho_4^2 - \varrho_5^2)}{\lambda_{\max}(\Gamma_i^{-1})}\Bigg)\Bigg\}$$

$$C_3 = \frac{1}{2}(\varsigma + 2\varrho_3^2)\sum_{i=1}^{n}\theta_i^T\theta_i + \frac{1}{2}\lambda_{\max}(K_1^T K_1)\bar{o}_c^2 + \bar{\epsilon}^2 + \frac{1}{2}\bigg(\frac{l^2}{\varrho_2^2} + \frac{\bar{\gamma}^2\|\varphi\|^2}{\varrho_4^2} + \lambda_{\max}(K_1^T K_1)\bigg)\bar{z}^2 + \frac{1}{2}\bar{p}^2 \quad (55)$$

To guarantee $\kappa_3 > 0$, controller parameters should be chosen to satisfy: $\min_{i=1,\ldots,n} k_i > 0$, $\lambda_{\min}\Big(2K_1 - (5 + \frac{5\bar{\gamma}^2\|\varphi\|^2}{\varrho_3^2} + \frac{l^2}{\varrho_5^2})I\Big) > 0$ and $\Big((\varsigma - \varrho_2^2 - 3\varrho_3^2 - \varrho_4^2 - \varrho_5^2)\Big) > 0$, where ϱ_2, ϱ_3, ϱ_4 and ϱ_5 are adjustable positive parameters. Then the following theorem is obtained.

Theorem 3: For robotic system (1), by designing adaptive neural network controller (43) with adaptive law (45) and state observer (42), the controller can ensure that all the error signals are UUB. Furthermore, z_1 eventually converges to the compact set defined as $\Omega_{z_1} := \Big\{z_1 \in \mathbb{R}^n \big| |z_{1i}| \le \sqrt{2e^{H_3}}, i = 1, \ldots, n\Big\}$, and z_2 eventually converges to the compact set defined as $\Omega_{z_2} := \Big\{z_2 \in \mathbb{R}^n \big| \|z_2\| \le \sqrt{\frac{2H_3}{\lambda_{\min(M)}}}\Big\}$, where $H_3 = V_3(0) + \frac{C_3}{\kappa_3}$.

Proof: The proof is similar to that of Theorem 1, so it will not be discussed in details.

IV. SIMULATION

In this section, we will verify the effectiveness of the proposed control by implementing the numerical simulation. A typical robot with three degrees of freedom is considered, and three degrees of freedom are three rotary degrees. The system matrixes of the robot given in (1) are given by

$$M = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \tag{56}$$

$$C = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix}, G = \begin{bmatrix} G_1 \\ G_2 \\ G_3 \end{bmatrix} \tag{57}$$

where $M_{11} = m_3 q_3^2 \sin^2(q_2) + p_1$; $D_{12} = p_2 q_3 \cos(q_2)$; $M_{13} = p_2 \sin(q_2)$; $M_{21} = p_2 q_3 \cos(q_2)$; $M_{22} = m_3 q_3^2 + I_2$; $M_{23} = 0$; $M_{31} = p_2 \sin(q_2)$; $M_{32} = 0$; $M_{33} = m_3$; $C_{11} = p_4 \dot{q}_2 + p_5 \dot{q}_3$; $C_{12} = p_4 \dot{q}_1 - p_3 q_3 p_8$; $C_{13} = p_5 \dot{q}_1 - p_3 p_6 q_3$; $C_{21} = -p_4 \dot{q}_1$; $C_{22} = m_3 q_3 \dot{q}_3$; $C_{23} = p_3 p_9 - m_3 q_3 \dot{q}_2$; $C_{31} = -p_5 \dot{q}_1 + p_3 p_{10}$; $C_{32} = m_3 q_3 \dot{q}_2 + p_3 p_{11}$; $C_{33} = 0$; $G_1 = 0$; $G_2 = -m_3 g q_3 \cos(q_2)$; $G_3 = -m_3 g \sin(q_2)$. where $p_1 = m_3 l_2^2 + m_2 l_1^2 + I_1$; $p_2 = m_3 l_2$; $p_3 = m_3 l_1$; $p_4 = m_3 q_3^2 \sin(q_2) \cos(q_2)$; $p_5 = m_3 q_3^2 \sin^2(q_2)$; $p_6 = \sin(q_2)\dot{q}_2$;$p_7 = \sin(q_2)\dot{q}_3$; $p_8 = p_6 + p_7$; $p_9 = \cos(q_2)\dot{q}_1$; $p_{10} = \cos(q_2)\dot{q}_2$ and $p_{11} = \cos(q_2)\dot{q}_3$. Parameters of the robotic system are defined in the table below.

Table 1: Parameters of the robot

Parameter	Description	Value
m_1	Mass of link 1	2.00 kg
m_2	Mass of link 2	1.00 kg
m_3	Mass of link 3	0.30 kg
l_1	Length of link 1	1.00 m
l_2	Length of link 2	0.20 m
l_3	Length of link 3	1.00 m
I_1	Inertia of link 1	0.5×10^{-3} kgm^2
I_2	Inertia of link 2	0.1×10^{-3} kgm^2

The detailed simulation results are given as follows.

A. Model-based Control Simulation Implementation

In this section, the effectiveness of model-based control (23) will be verified by simulation implementation. Initial values are set as: $x_1(0) = [0.05, 0.56, -0.05]^T$rad and $x_2(0) = [0, 0, 0]^T$rad/s. Controller parameters are chosen as follows: $K = \text{diag}[100, 100, 100]$, $K_1 = \text{diag}[10, 10, 10]$, $\mu_1^+ = 1$, $\mu_2^+ = 2$, $\mu_3^+ = 2$, $\mu_1^- = -2$, $\mu_2^- = -1$ and $\mu_3^- = -2$. Therefore observing (23), we know

$$-13Nm \leq \mu_1 \leq 12Nm \tag{58}$$

$$-12Nm \leq \mu_2 \leq 13Nm \tag{59}$$

$$-13Nm \leq \mu_3 \leq 13Nm \tag{60}$$

The reference trajectory of x_1 is set as $x_d = [0.5\sin(t), 0.6\cos(t), 0.7\sin(t)]^T$rad.

The detailed simulation results are given in Figs. 1-3. In Fig. 1, actual trajectory x_1 and reference trajectory x_d are plotted, respectively, and Fig. 1 also illustrates that x_1 fast converges to a small neighborhood of reference trajectory x_d, which shows that the tracking performance of the robot is satisfactory. In Fig. 2, tracking error z_1 is plotted, and it can be known that z_1 converges to a small neighborhood of zero with a satisfactory overshoot. In Fig. 3, control input μ is given and is constrained in the predefined region, i.e., $\mu_{ci}^- \leq \mu_i \leq \mu_{ci}^+$, $i = 1, 2, 3$, are satisfied.

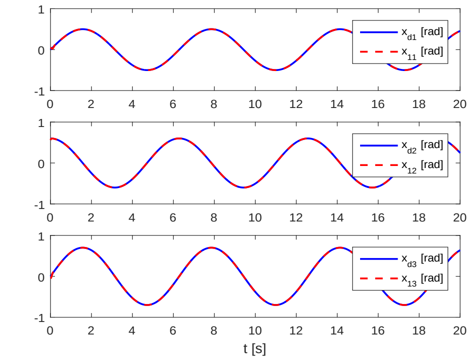

Fig. 1. Actual trajectory x_1 and reference trajectory x_d under model-based control (23).

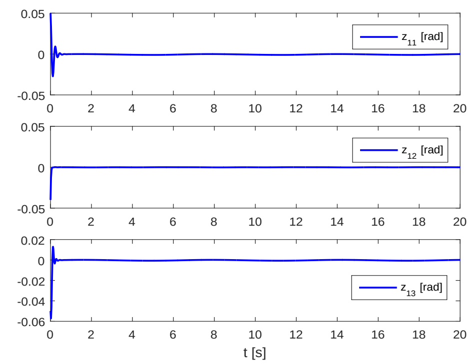

Fig. 2. Tracking error $z_1 = x_1 - x_d$ under model-based control (23).

B. State-Feedback-Based Adaptive Neural Control Simulation Implementation

In this section, the effectiveness of proposed control (30) will be verified by simulation implementation. The number of neural nodes is set as $l = 2^{12}$, the center of activation function $\psi(Z)$ is chosen in the area of $[-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1] \times [-1, 1]$. The width of centers is set as $\eta^2 = 1$. Initial values are set as $\hat{\theta}_1(0) = \hat{\theta}_2(0) = \hat{\theta}_3(0) = [0, \ldots, 0]^T \in \mathbb{R}^{2^{12}}$. The parameters of the updating law given in (32) are set as $\Gamma_1 = \text{diag}[100, 100, 100]$, $\Gamma_2 = \text{diag}[50, 50, 50]$, $\Gamma_3 = \text{diag}[100, 100, 100]$ and $\varsigma = 0.0001$. The rest of controller parameters are the same as those of section IV-A.

The detailed simulation results are given in Figs. 4-7. In Fig. 4, actual trajectory x_1 and reference trajectory x_d are plotted, respectively, and Fig. 4 shows that x_1 converges to a small neighborhood of reference trajectory x_d, which shows that the tracking performance of the robot is satisfactory. In Fig. 5, tracking error z_1 is given. Fig. 6 plots control input μ and furthermore μ is constrained in the the predefined region, i.e., $\mu_{ci}^- \leq \mu_i \leq \mu_{ci}^+$, $i = 1, 2, 3$, are satisfied. Fig. 7 gives the Euclidean norm of weight vector $\hat{\theta}_i$, $i = 1, 2, 3$. By observing the above-mentioned analysis, we know that although there exist unknown dynamics $M(q)$, $C(q, \dot{q})$ and $G(q)$, adaptive neural control (30) constrained within the predefined region, still makes the robot have a satisfactory tracking performance, which has been illustrated by simulation results.

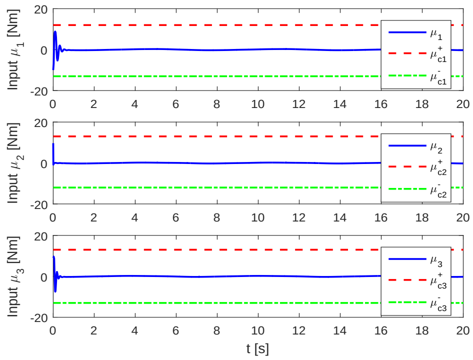

Fig. 3. Control input μ under model-based control (23).

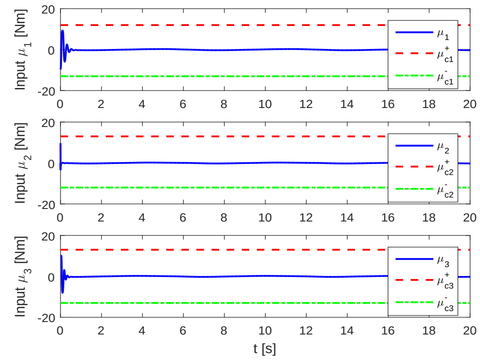

Fig. 6. Control input μ under state-feedback-based adaptive neural control (30).

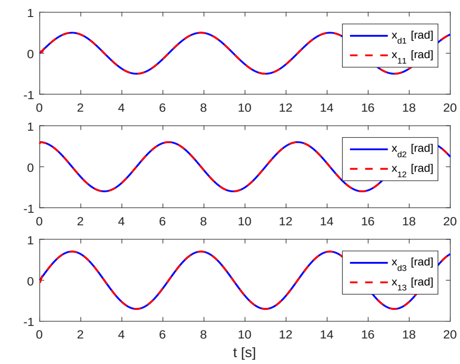

Fig. 4. Actual trajectory x_1 and reference trajectory x_d under state-feedback-based adaptive neural control (30).

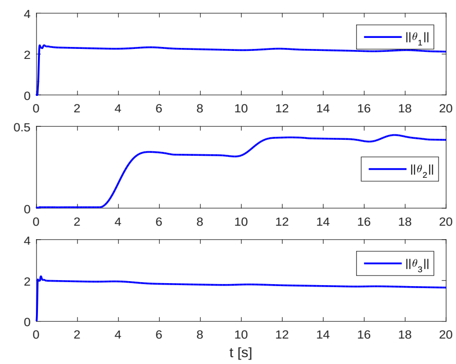

Fig. 7. Euclidean norm $\|\hat{\theta}_i\|, i = 1, 2, 3$ under state-feedback-based adaptive neural control (30).

C. Output-Feedback-Based Adaptive Neural Control Simulation Implementation

In this section, the effectiveness of proposed control (43) will be verified by simulation implementation. High-gain observer parameters are set as $\lambda_1 = 1$ and $\rho = 0.0007$. The rest of controller parameters are the same as those of section IV-B.

The detailed simulation results are given in Figs. 8-11. In Fig. 8, actual trajectory x_1 and reference trajectory x_d are plotted, respectively, and Fig. 8 also illustrates that x_1 converges to a small neighborhood of reference trajectory x_d, which shows that the tracking performance of the robot is satisfactory. In Fig. 9, tracking error z_1 is given. Fig. 10 plots control input μ which is constrained in the the predefined region, i.e., $\mu_{ci}^{-} \leq \mu_i \leq \mu_{ci}^{+}$, $i = 1, 2, 3$, have been guaranteed. Fig. 11 gives the Euclidean norm of weight vector $\hat{\theta}_i$, $i = 1, 2, 3$. By observing the above-mentioned analysis, we know that although there exist unknown dynamics $M(q)$, $C(q, \dot{q})$, $G(q)$ and immeasurable state x_2, proposed control (43) constrained within the predefined region, still makes the robot have a satisfactory tracking performance, which has been

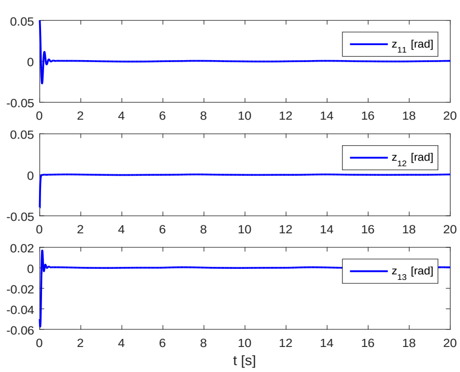

Fig. 5. Tracking error $z_1 = x_1 - x_d$ under state-feedback-based adaptive neural control (30).

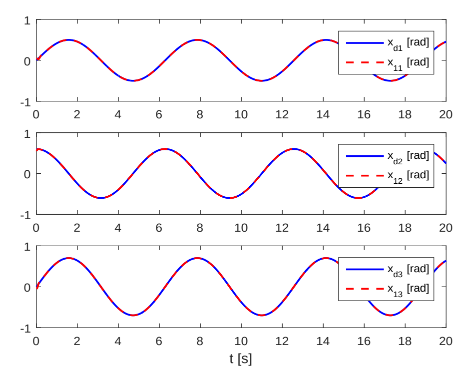

Fig. 8. Actual trajectory x_1 and reference trajectory x_d under output-feedback-based adaptive neural control (43).

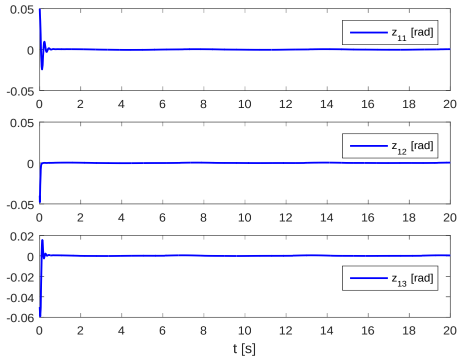

Fig. 9. Tracking error $z_1 = x_1 - x_d$ under output-feedback-based adaptive neural control (43).

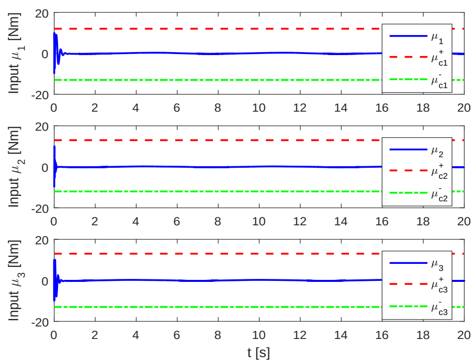

Fig. 10. Control input μ under output-feedback-based adaptive neural control (43).

illustrated by simulation results.

V. Conclusion

In this paper, an adaptive neural network bounded control scheme is developed for an n-link rigid robotic manipulator with unknown dynamics. For methods of dealing with saturation in [66]–[70], the bounds of the designed controller cannot be known *a prior* for the designer. In this paper, the bounds of the designed controller are known *a prior* and furthermore they can be changed by adjusting control gains, *making them applicable within actuator limitations*. Furthermore, it should be emphasized that the bounds of the designed controller are asymmetric. Neural networks are used to approximate unknown robotic dynamics. The effectiveness of the proposed scheme has been verified by simulation results. It should be emphasized that robots in practice are often required to move in a finite space, which illustrates that output constraint [75] should be guaranteed. Therefore, the optimal algorithm, such as parallel algorithm [76], [77], I-Ching divination evolutionary algorithm [78], [79] and dynamic programming [80]–[82], will be investigated for robots with output constraint in the future.

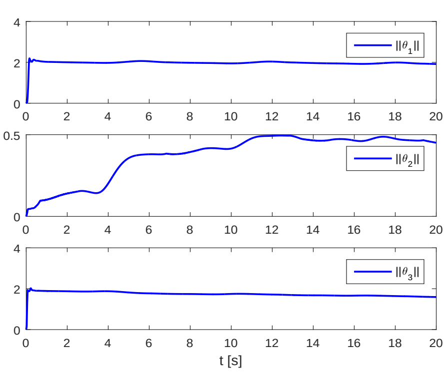

Fig. 11. Euclidean norm $\|\hat{\theta}_i\|, i = 1, 2, 3$ under output-feedback-based adaptive neural control (43).

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Appendix

Proof: Multiplying (28) by $e^{\kappa_1 t}$ equals $\frac{d(V_1 e^{\kappa_1 t})}{dt} \leq C_1 e^{\kappa_1 t}$. Integrating the above inequality, we get

$$V_1 \leq (V_1(0) - \frac{C_1}{\kappa_1})e^{-\kappa_1 t} + \frac{C_1}{\kappa_1} \leq V_1(0) + \frac{C_1}{\kappa_1} \tag{A.1}$$

Combining (21), we have

$$\ln(\cosh(z_{1i})) \leq \sum_{i=1}^{n} \ln(\cosh(z_{1i})) \leq V_1(0) + \frac{C_1}{\kappa_1} \tag{A.2}$$

$$\frac{1}{2}\lambda_{\min}(M)||z_2||^2 \leq \frac{1}{2} z_2^T M z_2 \leq V_1(0) + \frac{C_1}{\kappa_1} \tag{A.3}$$

Note that

$$\frac{1}{2} z_{1i}^2 \leq \cosh(z_{1i}) \tag{A.4}$$

we have

$$|z_{1i}| \leq \sqrt{2e^{H_1}}, \ i = 1, \ldots, n \tag{A.5}$$

$$||z_2||^2 \leq \frac{2H_1}{\lambda_{\min}(M)} \tag{A.6}$$

where $H_1 = V_1(0) + \frac{C_1}{\kappa_1}$. This finishes the proof.

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