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Global Adaptive Tracking Control of Robot Manipulators Using Neural Networks with Finite-time Learning Convergence

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Abstract: In this paper, the global adaptive neural control with finite-time (FT) convergence learning performance for a general class of nonlinear robot manipulators has been investigated. The scheme proposed in this paper offers a subtle blend of neural controller with robust controller, which palliates the limitation of neural approximation region to ensure globally uniformly ultimately bounded (GUUB) stability by integrating a switching mechanism. Moreover, the proposed scheme guarantees the estimated neural weights converging to optimal values in finite time by embedding an adaptive learning algorithm driven by the estimated weights error. The optimal weights obtained through the learning process of the neural networks (NNs) will be reused next time for repeated tasks, and can thus reduce computational load, improve transient performance and enhance robustness. The simulation studies have been carried out to demonstrate the superior performance of the controller in comparison to the conventional methods.

Keywords: Finite-time learning convergence, globally uniformly ultimate boundedness, neural networks, robot manipulators.

1. INTRODUCTION

In the last decades, robots have been widely used in various fields. With the rapid development and extensive applications of robotic technology, the requirements for fine working and flexible control are becoming increasingly demanding under different environments. However, due to the increasing complexity of dynamics model of robots, exact knowledge of robot dynamics is unavailable in actual engineering application. In addition, the working condition could be extremely uncertain, such as variation of the external environment and change of payload, etc. Thus, a crucial problem in robot control is to overcome the uncertainties mentioned above.

In practical industrial applications, there are many ways to overcome the uncertainties of the systems [1–5]. NNs [6] play a significant role to enhance robot's intelligence [7–14], by improvement of the performance of the control systems in uncertain environments. With the universal approximation ability, the NNs can be used as an effective tool in approximation based control of highly uncertain, nonlinear and complex systems. The approximation ability of the NNs lies on the foundation of the Stone-Weierstrass theorem [15–18], which states that any real continuous function on a compact set is able to be uniformly approximated to an arbitrary degree of accuracy.

NNs can be embeded into control framework in a variety of means [19–23], and remarkable achievements have been made. However, it is essential to note that the NNs approximation ability is valid merely in a compact domain. The conventional NN-based robot manipulators control could merely guarantee the semi-global uniformly ultimately bounded (SGUUB) stability. In this sense, it is ideal to grow a global NNs controller for robot manipulators [24]. In [25], the global NNs controller was only designed for strict-feedback systems in the case of existing unknown dynamics. To palliate the difficulty in prior estimation of the domain for the employment of the NNs, a robust adaptive NNs controller was addressed in [26] to achieve global uniformly ultimately bounded (GUUB)

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tracking.

It should also be noted that the conventional adaptive NNs controls only focus on control performance rather than neural learning performance. However, with conventional adaptive laws (e.g. gradient method, e-modification and σ-modification), it is not possible to guarantee that the learned neural weights converge to the optimal values. Moreover, the speed of the learning convergence cannot be specified by the designer. As a matter of fact, the estimation of NN weights usually do not converge to their optimal values. Therefore, neural learning has to be carried out each again next time even if for a repeated task.

In order to associate with conventional learning rate, the FT adaptive learning algorithm is employed to enhance neural learning performance. In [27, 28], the parameter estimation error was obtained by introducing a set of auxiliary filtered variables in a novel way. Therefore, adaptive laws established by the estimation error were presented to achieve the FT convergence. It is remarkable that the FT adaptive learning algorithm can also ensure that the estimated weights converge to optimal values in finite time. The optimal weights obtained through learning process of NNs could therefore be reused next time to repeat the same control task. In this way, the FT adaptive learning algorithm reduces computational load and enhances transient performance for a repeated control task. Consequently, the FT adaptive learning algorithm is of great importance in practical applications of NNs. Inspired by the aforementioned works, in this paper we will develop a global adaptive neural control approach using the NNs with the FT learning convergence, aiming at a general class of nonlinear robot manipulators with unknown dynamics. Based on the learning capability, RBF NNs [29–31] are employed to learn the unknown robot manipulators dynamics. To characterize the neural learning performance, the FT adaptive learning algorithm is presented to enhance neural learning performance. Moreover, a global adaptive neural control scheme is proposed to guarantee not only the global uniformly ultimately boundedness (GUUB) of all the signals in the closed-loop system, but also the neural learning performance such that the estimated neural weights converge to their optimal values in finite time. Consequently, the NNs could simply re-use the learned weights' values for a repeated task next time instead of re-learning them. Thus transient performance and robustness could be improved by skipping the neural learning process.

The remainder of this paper is outlined as follows: mathematical model of a robot manipulator is characterized in Section 2. Section 3 briefly introduces the concept and structure of the radial basis function neural networks (RBF NNs), as well as some functions and key lemmas which are crucial for the controller design. The global adaptive neural controller enhanced by FT learning convergence is designed in Section 4. In Section 5, the simulation results validate the approach we suggest is credible. Finally, Section 6 summarizes up the previous design.

2. PROBLEM FORMULATION

2.1. System description

The dynamics equation of an n-link robot manipulator can be described as follows:

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

where $q=[q_1,\dots,q_n]^T\in R^n$, $\dot{q}=[\dot{q}_1,\dots,\dot{q}_n]^T\in R^n$ and $\ddot{q}=[\ddot{q}_1,\dots,\ddot{q}_n]^T\in R^n$ represent the robot joint position vector, joint velocity vector and joint acceleration vector, respectively. $M(q)\in R^{n\times n}$, $V(q,\dot{q})\in R^{n\times n}$, and $G(q)\in R^n$ are the inertia matrix, Coriolis/centripetal torque matrix and gravity vector, respectively. According to [32], the following properties hold for the robotic system (1):

Property 1: The matrix $M(q)\in R^{n\times n}$ is symmetric positive-definite.

Property 2: The matrix $\dot{M}(q)-2C(q,\dot{q})$ is skew-symmetric, i.e., $z^T\left(\dot{M}-2C\right)z=0$, $\forall z\in R^n$.

Property 3: The matrices $M(q)$, $C(q,\dot{q})$ and $G(q)$ are all bounded.

2.2. System transformation

Define $x_{1i}=q_i$, $i=1,\dots n$, $x_1=[x_{11},\dots,x_{1n}]^T\in R^n$, and $x_{2i}=q_i, i=1,\dots n$, $x_2=[x_{21},\dots,x_{2n}]^T\in R^n$. An n-link robot manipulator (1) is a multiple-input-multiple-output (MIMO) vector functions system which can be transformed to the following form:

$$\begin{aligned}&\dot{x}_1=x_2,\\&M\dot{x}_2=-(Cx_2+G)+\tau,\\&y=x_1,\end{aligned} \tag{2}$$

where $y=x_1$ is the output of the robot manipulator system.

3. PRELIMINARIES

3.1. RBF neural networks

In this paper, the RBF NNs are employed as a universal approximator to emulate any real continuous function $f: R^M\to R$ with the following form:

$$f(X_{in})=\hat{f}(X_{in},W^*)+\varepsilon(X_{in}),\ \forall X_{in}\in\Omega_{X_{in}}, \tag{3}$$

where $\hat{f}(X_{in},\hat{W})=\hat{W}^TS(X_{in})$, with the input vector $X_{in}\in\Omega_{X_{in}}\subset R^M$, the NNs output $\hat{f}\in R$ is the estimation of f, $\hat{W}=[\hat{\omega}_1,\dots,\hat{\omega}_N]^T\in R^N$ is the weight parameter vector, and N is the number of NNs nodes. W^* is optimal NNs weights, According to [29], W^* is defined as:

$$W^*=\arg\min_{(W)}\left[\sup_{X_{in}\in\Omega_{X_{in}}}|f(X_{in})-\hat{f}(X_{in},\hat{W})|\right], \tag{4}$$

and $\varepsilon(X_{in})$ is the NNs approximation error, which is uniformly bounded by $|\varepsilon(X_{in})| \leq \varepsilon^*, \forall X_{in} \in \Omega_{X_{in}}$. $S(X_{in}) = [s_1(X_{in}), \ldots, s_N(X_{in})]^T$ is a nonlinear vector function of the inputs, the components of which have the following form:

$$s_i(X_{in}) = \exp\left[-\frac{(X_{in}-\xi_i)^T(X_{in}-\xi_i)}{\vartheta^2}\right], \; i = 1, \ldots, N, \tag{5}$$

where $\xi_i = [\xi_{i1}, \xi_{i2}, \ldots, \xi_{iM}]^T \in R^M$ represents the center of the ith basis function and ϑ represents the variance.

Assumption 1: The optimal weight W^* is bounded as $\|W^*\| \leq W_m$ on the compact $\Omega_{X_{in}}$.

Assumption 2: The reference signals q_d and their derivatives $\dot{q}_d$ are smooth and bounded functions.

3.2. Partial PE condition

In adaptive systems, the persistent excitation (PE) condition is of great significance, which has be proven that, the RBF NNs can achieve accurate approximation of closed-loop system dynamics in a neighborhood of a specific periodic trajectory with the partial PE condition [29], when tracking a reference periodic-like trajectory.

Definition 1 [27]**:** A vector or matrix $\Psi(t)$ is called persistently excited if there exist $T > 0$, $\varsigma > 0$, such that

$$\int_t^{t+T} \Psi^T(\tau)\Psi(\tau)d\tau \geq \varsigma I, \forall t \geq 0. \tag{6}$$

3.3. Useful functions and key lemmas

Lemma 1 [25]**:** The following inequality holds for any $\omega_0 > 0$ and $\eta \in R$:

$$0 \leqslant |\eta| - \eta \tanh\left(\frac{\eta}{\omega_0}\right) \leqslant \kappa\omega_0, \tag{7}$$

where κ is a constant satisfying $\kappa = e^{-(\kappa+1)}, i.e., \kappa = 0.2785$.

Lemma 2 [27]**:** For a continuous system $\dot{x} = f(x,t)$, $f(0,t) = 0$, $x \in R^n$, there is a continuously differentiable positive-definite function $V(x,t)$ and real numbers $\alpha_1 > 0$, $0 < \alpha_2 < 1$, such that when $\dot{V}(x,t) \leq -\alpha_1 V^{\alpha_2}(x,t)$ holds, then $V(x,t)$ converges to zero in finite time with the settling time $T \leq \left(\frac{1}{\alpha_1(1-\alpha_2)}\right) V^{1-\alpha_2}(x(t_0), t_0)$, for any given initial condition $x(t_0)$.

Definition 2 [25]**:** Given constants $0 < {}^1r_{j,i} < {}^2r_{j,i}, i = 1, \ldots, n$ and $j = 1, 2$, being the constants defining the boundaries of the compact subsets Ω_r, the set of switching functions is specified as below:

$$b_k(x_{k,i}) \triangleq \begin{cases} 1 & \text{if } |x_{k,i}| < {}^1r_{k,i} \\ \dfrac{{}^2r_{k,i}^2 - x_{k,i}^2}{{}^2r_{k,i}^2 - {}^1r_{k,i}^2} e^{\left(\frac{x_{k,i}^2 - {}^1r_{k,i}^2}{\varpi\left({}^2r_{k,i}^2 - {}^1r_{k,i}^2\right)}\right)^{2b}} & \\ & \text{if } {}^1r_{k,i} \leq |x_{k,i}| \leq {}^2r_{k,i} \\ 0 & \text{if } |x_{k,i}| > {}^2r_{k,i} \end{cases} \tag{8}$$

$$b_{j,i}(\bar{x}_j) \triangleq \prod_{k=1}^{j} b_k(x_{k,i}), \tag{9}$$

where $\bar{x}_1 = x_1^T \in R^n$, $\bar{x}_2 = \left[x_1^T, x_2^T\right]^T \in R^{2n}$, and $B_j(\bar{x}_j) = \mathrm{diag}(b_{j,1}(\bar{x}_j), .., b_{j,n}(\bar{x}_j))$, with $\varpi > 0$ and $b \geq 1$.

4. GLOBAL NEURAL CONTROL OF ROBOT MANIPULATOR

The global adaptive neural control with finite-time (FT) convergence learning performance for robot manipulators is investigated in this section. During the controller design, the procedure breaks down into two steps.

4.1. Controller design

Step 1: The robot manipulator joint position error is defined as $\tilde{x}_1 = x_1 - x_{1d}$, where $x_{1d} = q_d$. Taking the derivative of x_1 and using (2), we have:

$$\dot{\tilde{x}}_1 = \dot{x}_1 - \dot{x}_{1d} = x_2 - \dot{x}_{1d}, \tag{10}$$

where $\dot{x}_{1d} = \dot{q}_d$.

Take x_2 as the virtual control of (10) and design the signal x_{2d} as:

$$x_{2d} = -K_{11}\tilde{x}_1 - K_{12}\mathrm{sign}(\tilde{x}_1) + \dot{x}_{1d}, \tag{11}$$

where $K_{11} = \mathrm{diag}(k_{11,1}, \ldots, k_{11,n})$, and $k_{11,i} > 0, i = 1, \ldots, n$, $K_{12} = \mathrm{diag}(k_{12,1}, \ldots, k_{12,n})$, and $k_{12,i} > 0, i = 1, \ldots, n$.

Then define $\tilde{x}_2 = x_2 - x_{2d}$ and (10) is calculated as:

$$\begin{aligned} \dot{\tilde{x}}_1 &= x_2 - \dot{x}_{1d} \\ &= x_2 - x_{2d} + x_{2d} - \dot{x}_{1d} \\ &= \tilde{x}_2 - K_{11}\tilde{x}_1 - K_{12}\mathrm{sign}(\tilde{x}_1). \end{aligned} \tag{12}$$

Step 2: The robot manipulator joint velocity error is written as $\tilde{x}_2 = x_2 - x_{2d}$. Taking the derivative of x_2 and using (2), we have:

$$M\dot{\tilde{x}}_2 + C\tilde{x}_2 = \tau - M\dot{x}_{2d} - Cx_{2d} - G. \tag{13}$$

The vector $M\dot{\tilde{x}}_2$ in (13) is a function of the robot manipulator joint acceleration $\ddot{q}$, which is sensitive to measurement noise. To make control design independent of joint acceleration, inspired by [27], the Eq. (13) can be rewritten as:

$$\dot{F}_1(z) + F_2(z) = \tau + F_3(z), \tag{14}$$

where $F_1 = M\tilde{x}_2$, $F_2 = -\dot{M}\tilde{x}_2 + C\tilde{x}_2$ and $F_3 = -M\dot{x}_{2d} - Cx_{2d} - G$. Using NNs to emulate the unknown functions F_1, F_2 and F_3, respectively, we have:

$$\begin{aligned} F_1 &= M\tilde{x}_2 = W_1^{*T}S_1(z) + \varepsilon_1, \\ F_2 &= -\dot{M}\tilde{x}_2 + C\tilde{x}_2 = W_2^{*T}S_2(z) + \varepsilon_2, \\ F_3 &= -M\dot{x}_{2d} - Cx_{2d} - G = W_3^{*T}S_3(z) + \varepsilon_3, \end{aligned} \tag{15}$$

where $z = [q, \dot{q}, x_{2d}, \dot{x}_{2d}]$, and W_1^{*T}, W_2^{*T} and W_3^{*T} are the optimal NNs weights matrix, S_1, S_2 and S_3 are the basis

function vectors, while ε_1, ε_2 and ε_3 are the NNs construction error, and $\|\varepsilon_1\| < \varepsilon_1^*$, $\|\varepsilon_2\| < \varepsilon_2^*$, $\|\varepsilon_3\| < \varepsilon_3^*$.
Then, equation (15) can be further formulated as:

$$\begin{aligned} F_{1,i} =& \quad S_1^T W_{1,i}^* + \varepsilon_{1,i}, \\ F_{2,i} =& \quad S_2^T W_{2,i}^* + \varepsilon_{2,i}, \\ F_{3,i} =& \quad S_3^T W_{3,i}^* + \varepsilon_{3,i}, \end{aligned} \tag{16}$$

where $i = 1, ..., n$. $W_{1,i}^*$, $W_{2,i}^*$ and $W_{3,i}^*$ are ith column of the matrices W_1^*, W_2^* and W_3^*, respectively.

Consequently, using RBFNNs method, the Eq. (14) can be divided into n subsystems as:

$$\dot{S}_1^T W_{1,i}^* + \dot{\varepsilon}_{1,i} + S_2^T W_{2,i}^* + \varepsilon_{2,i} - S_3^T W_{3,i}^* - \varepsilon_{3,i} = \tau_i. \tag{17}$$

Define a new weight matrix as follows:

$$W_i^* = \left[W_{1,i}^{*T} W_{2,i}^{*T} W_{3,i}^{*T}\right]^T = \begin{bmatrix} W_{1,i}^* \\ W_{2,i}^* \\ W_{3,i}^* \end{bmatrix}. \tag{18}$$

Consequently, the Eq. (17) can be formulated as:

$$\bar{S}^T W_i^* + \bar{\varepsilon}_i = \tau_i, \tag{19}$$

where $\bar{S}^T = \dot{\bar{S}}_1^T + \bar{S}_2^T - \bar{S}_3^T$ and $\dot{\bar{S}}_1 = \left[\dot{S}_1^T, \mathbf{0}_N^T, \mathbf{0}_N^T\right]^T$, $\bar{S}_2 = \left[\mathbf{0}_N^T, S_2^T, \mathbf{0}_N^T\right]^T$, $\bar{S}_3 = \left[\mathbf{0}_N^T, \mathbf{0}_N^T, S_3^T\right]^T$, $N_{\bar{S}} = N + N + N$, $\bar{\varepsilon}_i = \dot{\varepsilon}_{1,i} + \varepsilon_{2,i} - \varepsilon_{3,i}$.

We can design an adaptive controller as:

$$\begin{aligned} \tau_i =& -\tilde{x}_{1,i} - k_{21,i}\tilde{x}_{2,i} - k_{22,i}\mathrm{sign}\left(\tilde{x}_{2,i}\right) - b_{2,i}(\tilde{x}_2)u_i^N \\ & - \left(1 - b_{2,i}(\tilde{x}_2)\right)u_i^R, \ i = 1, ..., n, \end{aligned} \tag{20}$$

$$u_i^N = \hat{W}_i^T \bar{S}_3(z), \tag{21}$$

$$u_i^R = F_{3,i}^U(z)\tanh\left(\frac{F_{3,i}^U(z)}{\omega_2}\right), \tag{22}$$

where $K_{21} = \mathrm{diag}(k_{21,1}, ..., k_{21,n})$, and $k_{21,i} > 0, i = 1, ..., n$, $K_{22} = \mathrm{diag}(k_{22,1}, ..., k_{22,n})$, and $k_{22,i} > 0, i = 1, ..., n$. $F_{3,i}^U(z)$ is upper bound of $F_{3,i}(z)$.

To facilitate weights estimation, let us first design the following filters:

$$\begin{cases} \rho\dot{\bar{S}}_{1f} + \bar{S}_{1f} = \bar{S}_1, & \bar{S}_{1f}\mid_{t=0} = \mathbf{0}_{N_{\bar{S}}}, \\ \rho\dot{\bar{S}}_{2f} + \bar{S}_{2f} = \bar{S}_2, & \bar{S}_{2f}\mid_{t=0} = \mathbf{0}_{N_{\bar{S}}}, \\ \rho\dot{\bar{S}}_{3f} + \bar{S}_{3f} = \bar{S}_3, & \bar{S}_{3f}\mid_{t=0} = \mathbf{0}_{N_{\bar{S}}}, \\ \rho\dot{\tau}_{if} + \tau_{if} = \tau_i, & \tau_{if}\mid_{t=0} = 0_n, \end{cases} \tag{23}$$

where $\bar{S}_{1f}$, $\bar{S}_{2f}$, $\bar{S}_{3f}$ and τ_{if} are the filtered version of $\bar{S}_1$, $\bar{S}_2$, $\bar{S}_3$ and τ_i, respectively. According to (19) and (23), one can obtain:

$$W_i^{*T}\left(\frac{\bar{S}_1 - \bar{S}_{1f}}{\rho} + \bar{S}_{2f} - \bar{S}_{3f}\right) = W_i^{*T}\bar{S}_f = \tau_{if} - \bar{\varepsilon}_{if}. \tag{24}$$

Let us introduce matrices $P \in R^{N_{\bar{S}} \times N_{\bar{S}}}$, $Q_i \in R^{N_{\bar{S}}}$, which are defined as below:

$$\begin{cases} \dot{P} = -\ell P + \bar{S}_f\bar{S}_f^T, \\ \dot{Q}_i = -\ell Q_i + \bar{S}_f\tau_{if}, \end{cases} \tag{25}$$

where $\ell > 0$ is design parameter. The solution of (25) is derived as:

$$\begin{cases} P(t) = \int_0^t e^{-\ell_i(t-r)}\bar{S}_f\bar{S}_f^T dr, \\ Q_i(t) = \int_0^t e^{-\ell_i(t-r)}\bar{S}_f\tau_{if} dr, \end{cases} \tag{26}$$

Let us now define auxiliary vector $E_i \in R^N$ which can be calculated from P, Q_i:

$$\begin{aligned} E_i &= P\hat{W}_i - Q_i \\ &= P\hat{W}_i - PW_i^* - \psi_i \\ &= -P\tilde{W}_i - \psi_i, \end{aligned} \tag{27}$$

where $Q_i = PW_i^* + \psi_i$ with $\psi_i = \int_0^t e^{-\ell_i(t-r)}\bar{S}_f\bar{\varepsilon}_{if} dr$.

The closed-loop error equation becomes:

$$\begin{aligned} M\dot{\tilde{x}}_2 + C\tilde{x}_2 =& -\tilde{x}_1 - K_{21}\tilde{x}_2 - K_{22}\mathrm{sign}\left(\tilde{x}_2\right) \\ & + B_2(\tilde{x}_2)\left(\tilde{F}_3 + \varepsilon_3\right) \\ & + \left(I - B_2(\tilde{x}_2)\right)\left(F_3 - u^R\right), \end{aligned} \tag{28}$$

where $\tilde{F}_{3,i} = \tilde{W}_{3,i}^T S_3(z) = \tilde{W}_i^T\bar{S}_3(z)$, $\tilde{W}_{3,i} = W_{3,i}^* - \hat{W}_{3,i}$, $\tilde{W}_i = W_i^* - \hat{W}_i$.

The adaptation laws of the estimated parameters are designed as:

$$\dot{\hat{W}}_i = \Gamma\left(\bar{S}_3\tilde{x}_{2,i}b_{2,i}(\tilde{x}_2) - \delta_i\frac{P^T E_i}{\|E_i\|}\right), \ i = 1, ..., n, \tag{29}$$

where Γ is a symmetric positive definitive matrix, δ_i is designed positive parameter.

4.2. Stability analysis

Consider system (1), with control laws (20), and adaptive laws (29) under **Assumptions 1** and **2**. Let us choose a suitable Lyapunov function as below:

$$V = V_1 + V_2, \tag{30}$$

with

$$V_1 = \frac{1}{2}\tilde{x}_1^T\tilde{x}_1, \tag{31}$$

$$V_2 = \frac{1}{2}\tilde{x}_2^T M\tilde{x}_2 + \frac{1}{2}\sum_{i=1}^n\left(E_i^T P^{-1}\Gamma^{-1}P^{-1}E_i\right), \tag{32}$$

where Γ^{-1} is a positive-definite matrix.

Taking the derivative of V_1, we have:

$$\begin{aligned} \dot{V}_1 &= \tilde{x}_1^T\dot{\tilde{x}}_1 \\ &= \tilde{x}_1^T\left(\tilde{x}_2 - K_{11}\tilde{x}_1 - K_{12}\mathrm{sign}\left(\tilde{x}_1\right)\right) \\ &= -\tilde{x}_1^T K_{11}\tilde{x}_1 - \sum_{i=1}^n\left(k_{12,i}|\tilde{x}_{1,i}|\right) + \tilde{x}_1^T\tilde{x}_2 \\ &\le -\sum_{i=1}^n\left(k_{12,i}|\tilde{x}_{1,i}|\right) + \tilde{x}_1^T\tilde{x}_2 \\ &\le -K_1^*\sqrt{V_1} + \tilde{x}_1^T\tilde{x}_2, \end{aligned} \tag{33}$$

where $K_1^* = \sqrt{2}\lambda_{min}(K_{12})$.

According to (27), we have:

$$\begin{aligned}\frac{\partial(P^{-1}E_i)}{\partial t} &= -\frac{\partial(\tilde{W}_i + P^{-1}\psi_i)}{\partial t} \\ &= -\dot{\tilde{W}}_i + P^{-1}\dot{P}P^{-1}\psi_i - P^{-1}\dot{\psi}_i \\ &= -\dot{\tilde{W}}_i + \psi_i' \\ &= \dot{\hat{W}}_i + \psi_i',\end{aligned} \tag{34}$$

where $\psi_i' = P^{-1}\dot{P}P^{-1}\psi_i - P^{-1}\dot{\psi}_i$.

Taking the derivative of V_2 yields:

$$\begin{aligned}\dot{V}_2 =& \tilde{x}_2^T M\dot{\tilde{x}}_2 + \frac{1}{2}\tilde{x}_2^T \dot{M}\tilde{x}_2 \\ &+ \sum_{i=1}^{n}\left(E_i^T P^{-1}\Gamma^{-1}\left(\dot{\hat{W}}_i + \psi_i'\right)\right) \\ =& \frac{1}{2}\tilde{x}_2^T\dot{M}\tilde{x}_2 - \tilde{x}_2^T C\tilde{x}_2 - \tilde{x}_2^T\tilde{x}_1 - \tilde{x}_2^T K_{21}\tilde{x}_2 \\ &- \sum_{i=1}^{n}\left(k_{22,i}|\tilde{x}_{2,i}|\right) + \tilde{x}_2^T B_2(\bar{x}_2)\left(\tilde{F}_3 + \varepsilon_3\right) \\ &+ \tilde{x}_2^T\left(I - B_2(\bar{x}_2)\right)\left(F_3 - u^R\right) \\ &+ \sum_{i=1}^{n}\left(E_i^T P^{-1}\Gamma^{-1}\dot{\hat{W}}_i\right) \\ &+ \sum_{i=1}^{n}\left(E_i^T P^{-1}\Gamma^{-1}\psi_i'\right).\end{aligned} \tag{35}$$

Substituting the adaptation laws (29) into (35), we have:

$$\begin{aligned}\dot{V}_2 =& -\tilde{x}_2^T\tilde{x}_1 - \tilde{x}_2^T K_{21}\tilde{x}_2 - \sum_{i=1}^{n}\left(k_{22,i}|\tilde{x}_{2,i}|\right) \\ &+ \tilde{x}_2^T B_2(\bar{x}_2)\varepsilon_3 + \tilde{x}_2^T\left(I - B_2(\bar{x}_2)\right)\left(F_3 - u^R\right) \\ &+ \sum_{i=1}^{n}\left(-\psi_i^T P^{-1}\bar{S}_3\tilde{x}_{2,i}B_{2,i}(\bar{x}_2)\right) \\ &+ \sum_{i=1}^{n}\left(E_i^T P^{-1}\Gamma^{-1}\psi_i' - \delta_i\frac{E_i^T P^{-1}P^T E_i}{\|E_i\|}\right).\end{aligned} \tag{36}$$

The following inequalities hold:

$$\begin{aligned}&\tilde{x}_2^T B_2(\bar{x}_2)\varepsilon_3 \le \sum_{i=1}^{n}\left(\varepsilon_{3,i}^*|\tilde{x}_{2,i}|\right), \\ &F_{3,i} - u_{2,i}^R \le |F_{3,i}| - F_{3,i}^U\tanh\left(\frac{F_{3,i}^U}{\omega_2}\right) \le \kappa\omega_2.\end{aligned} \tag{37}$$

Using the Young inequality, we have:

$$\begin{aligned}\dot{V}_2 \le& -\tilde{x}_2^T\tilde{x}_1 - \tilde{x}_2^T K_{21}\tilde{x}_2 - \sum_{i=1}^{n}\left(k_{22,i}|\tilde{x}_{2,i}|\right) \\ &+ \sum_{i=1}^{n}\left(\varepsilon_{3,i}^*|\tilde{x}_{2,i}|\right) + \sum_{i=1}^{n}\left(\kappa\omega_2|\tilde{x}_{2,i}|\right) \\ &- \sum_{i=1}^{n}\left(|\tilde{x}_{2,i}|\|\psi_i^T P^{-1}\bar{S}_3\|\right) \\ &- \sum_{i=1}^{n}\left(\|E_i^T\|\left(\delta_i - \|P^{-1}\Gamma^{-1}\psi_i'\|\right)\right) \\ \le& -\sum_{i=1}^{n}\left(|\tilde{x}_{2,i}|\left(k_{22,i} - \varepsilon_{3,i}^* - \kappa\omega_2 + \|\psi_i^T P^{-1}\bar{S}_3\|\right)\right) \\ &- \sum_{i=1}^{n}\left(\|E_i^T\|\left(\delta_i - \|P^{-1}\Gamma^{-1}\psi_i'\|\right)\right) - \tilde{x}_2^T\tilde{x}_1 \\ \le& -K_2^*\sqrt{V_2} - \tilde{x}_1^T\tilde{x}_2,\end{aligned} \tag{38}$$

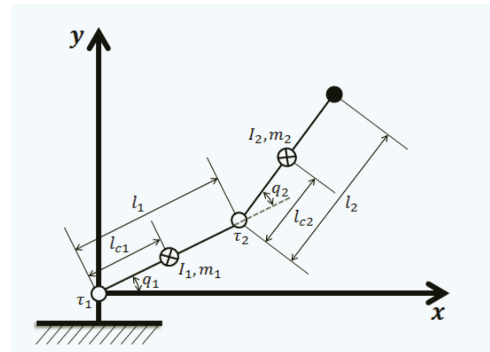

Fig. 1. Illustration of the 2DOF robot manipulator.

where $K_2^* = \min[(k_{22,i} - \varepsilon_{3,i}^* - \kappa\omega_2 + \|\psi_i^T P^{-1}\bar{S}_3\|) \times \sqrt{2/\lambda_{max}(M)}, (\delta_i - \|P^{-1}\Gamma^{-1}\psi_i'\|)\delta_p\sqrt{\lambda_{max}(\Gamma^{-1})}]$.

$$\dot{V} = \dot{V}_1 + \dot{V}_2 \le -K^*\sqrt{V}, \tag{39}$$

where $K^* = \min[K_1^*, K_2^*]$.

Note that the inequation (39) satisfies the condition of Lemma 2. Therefore, the error terms $\tilde{x}_1$, $\tilde{x}_2$ and E_i, $i = 1, \ldots, n$, converge to zero in finite time. Moreover, the parameter error $\tilde{W}$ converges to a compact set in finite time satisfying $\lim_{t\to\infty} P\tilde{W}_i = -\psi_i$. Then, $V \equiv 0$, $\forall t > t_c$ with the finite-time

$$t_c \le 2K^*\sqrt{V(0)}. \tag{40}$$

The tracking errors $\tilde{x}_1$ and $\tilde{x}_2$ vanish to zeros in finite time, so that the tracking error $\tilde{x}_1$, $\tilde{x}_2$ to zero is guaranteed.

Remark 1: According to [33] [34], the dissipativity and l_2-l_∞ approaches can be incorporated into the Lyapunov function to ensure the robustness.

5. SIMULATIONS STUDIES

Contrast simulation studies have been carried out on a model of 2DOF robot manipulator to analyze the effectiveness of the controller we developed above.

The dynamics of 2DOF robot manipulator is described as:

$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22}\end{bmatrix}\ddot{q} + \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22}\end{bmatrix}\dot{q} + \begin{bmatrix} G_1 \\ G_2\end{bmatrix} = \tau, \tag{41}$$

where $m_1 = 2$ kg, $m_2 = 0.85$ kg, $l_1 = 0.35$ m, $l_2 = 0.31$ m, $I_1 = 0.061$ kgm^2 and $I_2 = 0.020$ kgm^2. The m_i is the inertia of link i, I_i is the inertia of link i around the axis at the mass center of link i, l_i and l_{ci} are the length of link i and the distance between $i-1$th joint and the ith joint's mass center, $i = 1, 2$, respectively.

Table 1. The description of 2-joint robot manipulator.

M_{11}	$m_1 l_{c1}^2 + m_2(l_1^2 + l_{c2}^2 + 2l_1 l_{c2}\cos q_2) + I_1 + I_2$
M_{12}	$m_2(l_{c2}^2 + l_1 l_{c2}\cos q_2) + I_2$
M_{21}	$m_2(l_{c2}^2 + l_1 l_{c2}\cos q_2) + I_2$
M_{22}	$m_2 l_{c2}^2 + I_2$
V_{11}	$-m_2 l_1 l_{c2}\dot{q}_2 \sin q_2$
V_{12}	$-m_2 l_1 l_{c2}(\dot{q}_1 + \dot{q}_2)\sin q_2$
V_{21}	$m_2 l_1 l_{c1}\dot{q}_1 \sin q_2$
V_{22}	0
G_1	$(m_1 l_{c2} + m_2 l_1) g \cos q_1 + m_2 l_{c2} g \cos(q_1 + q_2)$
G_2	$m_2 l_{c2} g \cos(q_1 + q_2)$

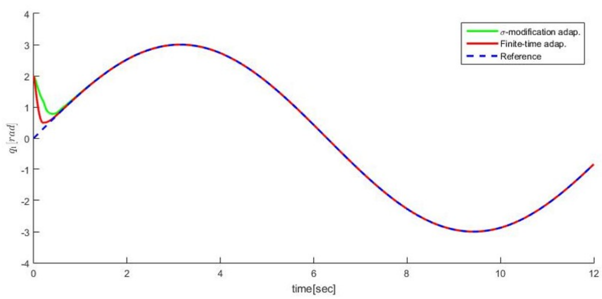

Fig. 2. Tracking performance of q_1.

The desired trajectories are given as $q_{d1} = 3\sin 0.5t$ and $q_{d2} = 2\cos 0.5t$, where $t \in [0, t_f]$, and $t_f = 15$s. The control gains are selected as $K_{11} = \text{diag}(10, 10)$, $K_{12} = \text{diag}(0.0001, 0.0001)$, $K_{21} = \text{diag}(10, 10)$, $K_{21} = \text{diag}(0.0001, 0.0001)$. And the NNs adaptive laws are chosen as $\Gamma_F = 15I$, $\Gamma_H = 15I$, $\delta_F = 0.005$, $\delta_H = 0.005$. The number of hidden layer nodes of the NNs is set as $N_1 = N_2 = N_3 = 256$. The NNs weight matrix are initialized as $\hat{W}_1(0) = \mathbf{0} \in R^{768}$, $\hat{W}_2(0) = \mathbf{0} \in R^{768}$. The robust parameters are set as $\omega_2 = 0.01$, while ${}^1r_{1,1} = {}^1r_{1,2} = {}^1r_{2,1} = {}^1r_{2,2} = 2$ and ${}^2r_{1,1} = {}^2r_{1,2} = {}^2r_{2,1} = {}^2r_{2,2} = 3$, and $\varpi = 1$ and $b = 1$. In the comparative simulation studies, the σ-modification adaptive laws is given as:

$$\dot{\hat{W}}_i = \Gamma\left(\bar{S}_3 \tilde{x}_{2,i} b_{2,i}(\bar{x}_2) - \sigma_i \hat{W}_i\right). \tag{42}$$

The simulation results are presented in Figs. 2-9.

Figs. 2-5 show that the reference signal q_d and $\dot{q}_d$ can be tracked in finite time. As it can be seen, all adaptation laws could lead to stable control performance. However, comparing with the conventional adaptive law, the global adaptive neural control with FT learning adaptive laws (30) achieve faster convergence speed of the tracking errors. It may be due to the employment of the derived weights error information E_i for the adaptive law.

Therefore, the proposed global adaptive neural controller for robot manipulators is able to achieve good transient tracking performance of tracking errors in the presence of unknown dynamics.

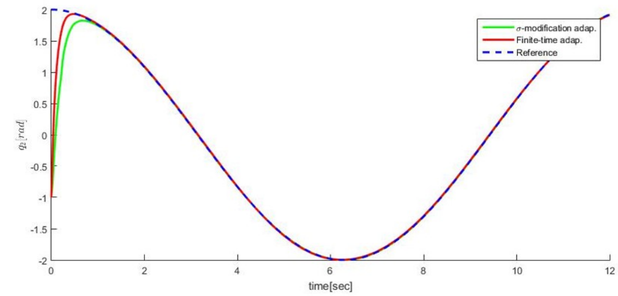

Fig. 3. Tracking performance of q_2.

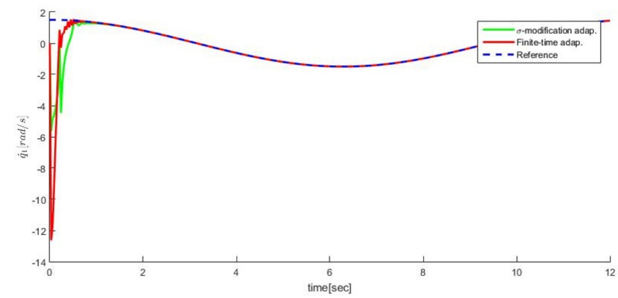

Fig. 4. Tracking performance of $\dot{q}_1$.

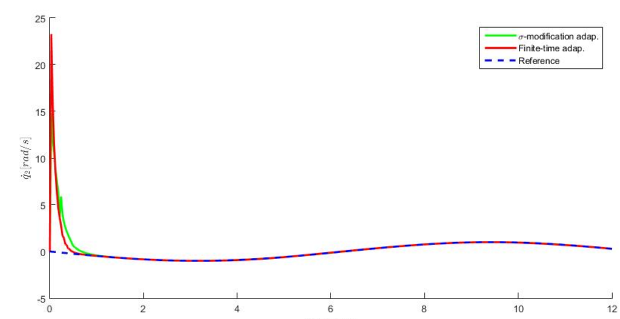

Fig. 5. Tracking performance of $\dot{q}_2$.

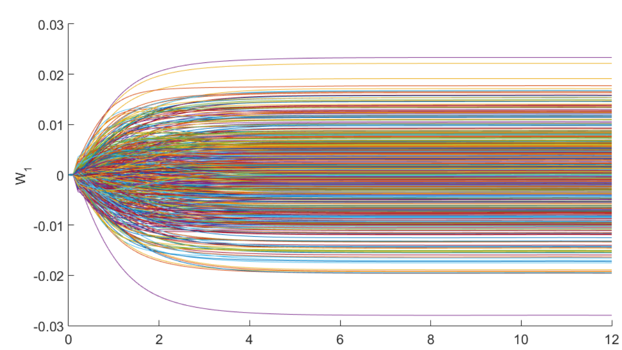

Fig. 6. FT weights update for the 1st joint.

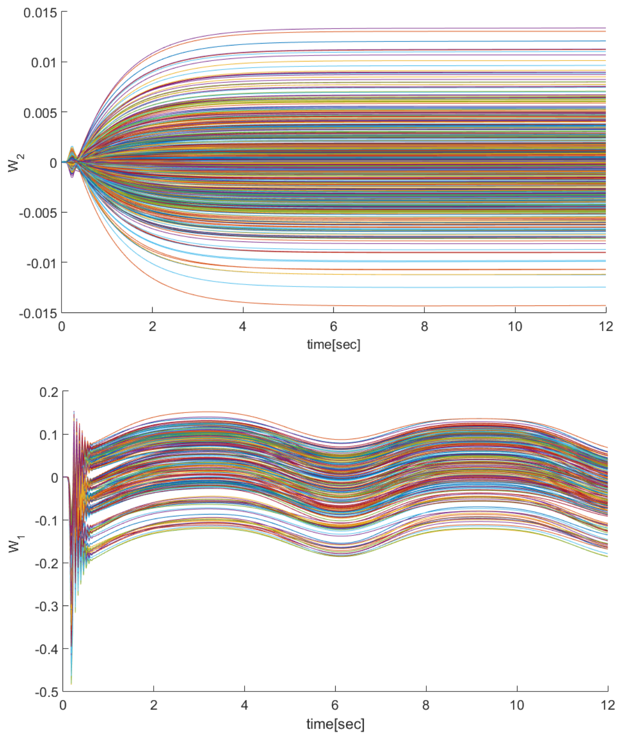

Fig. 8. Conventional weights update for the 1st joint.

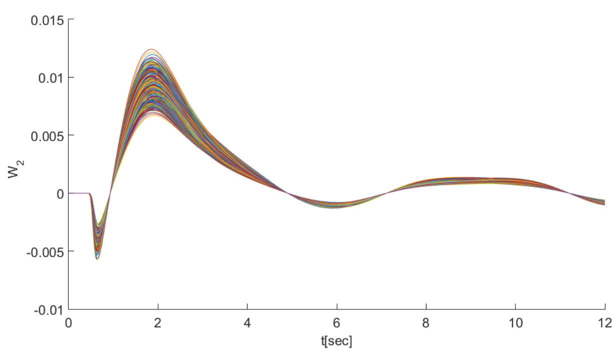

Fig. 9. Conventional weights update for the 2nd joint.

Figs. 6-7 show the weights converge to the optimal value in finite time. In comparison to the results shown in Figs. 8-9, the FT adaptive learning algorithm ensures that the adaptation of weights estimation converges to the optimal value in a prescribed time horizon, such that the learning weights can be reused for repeated task, and thus could reduce computational load, improve transient performance and enhance robustness.

6. CONCLUSIONS

In this work, a smooth switching algorithm has been employed by which adaptive neural controller and robust controller cooperate to ensure closed-loop system global stability as rigorously established by the Lyapunov approach. The FT adaptive learning algorithms are employed to guarantee that the estimated weights converge to optimal values in finite time. The optimal weights obtained through learning process of NNs could be reused next time for a repeated task, such that neural learning could be spared and thus transient control performance and robustness could be improved. In future work, we will extend the proposed scheme to more general nonlinear systems to test the performance of the proposed control method for more complex systems such as hypersonic flight vehicles [35–37].

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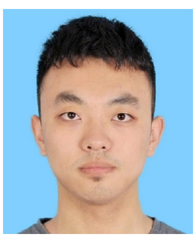

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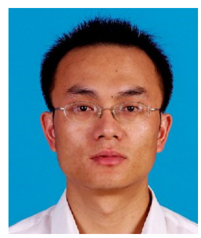

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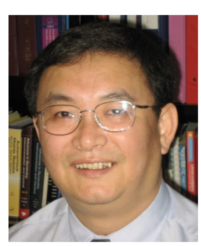

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