Hindawi
Complexity
Volume 2018, Article ID 8275296, 10 pages
https://doi.org/10.1155/2018/8275296

Research Article

Fuzzy Adaptive Switching Control for an Uncertain Robot Manipulators with Time-Varying Output Constraint

Yongqing Fan, Wenqing Wang, Ying Liu, and Minjuan Wang

School of Automation, Xi'an University of Posts and Telecommunications, Xi'an, China

Correspondence should be addressed to Yongqing Fan; fanyongqing@xupt.edu.cn

Received 29 March 2018; Accepted 17 May 2018; Published 22 July 2018

Academic Editor: Andy Annamalai

An adaptive control strategy based on a fuzzy logic system by introducing a nonzero time-varying parameter is studied for an n-link manipulator system with the condition of a complex environment. At the beginning, a universal approximator with a one time-varying parameter is proposed based on the analysis of the fuzzy logic system, which is utilized to equalize uncertainties in robot manipulators with time-varying output constraints. The novel design method is used to reduce greatly the online learning computation burden compared with traditional fuzzy adaptive control. The output and the position of robotic manipulators are constrained with time-varying, a good tracking performance can be guaranteed with the condition of unknown dynamics of robot manipulators, and the violation of constraints can be conquered by the analysis based on the barrier Lyapunov function. A switching adaptive control is proposed to extend the semiglobal stability to global stability. Effectiveness of the approach is demonstrated by simulation results.

1. Introduction

In recent decades, more challenges in an intelligent controller design or learning algorithms are urgent to be developed for the growing different applications in engineering environments. Intelligent technologies for manifold aims as a hot topic research and development emerged in many different regions or fields, like robotics and automation [1, 2], manufacturing [3], process industries [4], and so on. Accordingly, the intelligent control has become a formidable problem owing to the different environment in complex systems. Especially in various sophisticated scenarios, intelligent control is a challenging issue because of the various changes of the target object or other complicated phenomenon. In [5], an intelligent shared control system combined with human-computer interaction and a brain computer interface was developed. Based on a spatiotemporal context learning algorithm, good tracking performance can be achieved for various challenging environments in [6]. Under the condition of a sophisticated environment, a coupling interface proposed to learn human adaptive skills in [7]. Extreme learning machine (ELM) was employed to compensate for the uncertain nonlinearities of manipulator systems or be used to the robot teaching systems such that satisfactory performance can be achieved in [8, 9].

Adaptive technologies play a pivotal role in dealing with controlled systems in various complex environments and received more favor by scholars. Uncertain nonlinearities or unknown models commonly existed in systems with many complex environments; thus, fuzzy logic systems (FLSs) or neural networks (NNs) are employed to tackle with the performance indicators of the systems. Especially, FLSs and NNs are universal approximators [10–14], which can be used to approximate unknown terms by combining with an adaptive algorithm technique. In [15], a novel teleoperation control combining with NNs and wave variable is proposed to guarantee the stability of the closed-loop systems. For the unknown parameters of robotic systems, adaptive estimation design methods are developed in [16, 17]. For uncertain multiagent systems, adaptive NN synchronization controls by using the information of the neighboring agents are established in [18]. A new idea of finite-time quantized feedback control with NNs is addressed for quantized nonlinear systems with unknown states in [19]. Tracking controllers with prescribed performance are constructed for dynamical nonlinear systems in [20–23]. A variety of different forms of control technologies are designed for robot manipulators with unknown dynamics based on NNs or FLSs, like output feedback control [24–27], robust position control [28], decentralized control [29, 30], and so on. Nevertheless, it should be noted that the problem of constraint control was not considered in these literatures.

A barrier function as a useful tool was firstly proposed to protect the boundary on the feasible region in [31, 32], and this pioneer work induced many excellent research results in preventing constraint violation. For example, constant output constraint can be ensured by the analysis of the barrier Lyapunov function (BLF) in [33–35]. An adaptive neural tracking controller is designed by the stability of the integral barrier Lyapunov functions for robot manipulators in [36]. Adaptive fuzzy output controllers united in wedlock backstepping are also be proposed in [37–41]. Adaptive controls by employing the BLF are developed for a class of nonlinear systems with full-state constraints in [40, 41]. However, it should be pointed out that the output constraint is assumed to be a constant value in these references [33–41], and thus, these methods will be invalided for time-varying output constraints.

In many special complex work environments, varying constraints are necessary to be taken into account for meeting specific predefined targets, so how to exploit some novelty controls is essential. In [42], an asymmetric bimanual coordinate control based on a novel BLF with the position and velocity constraints in tasks is developed, which can be used to make the robot behavior adaptive and flexible to detect human operator motion. In [11], time-varying constraints are considered, and an adaptive neural network control of robot manipulators is designed to satisfy the tracking performance. It should be needed to point out that these above-mentioned NN or FLS control methods only have been guaranteed for semiglobal uniformly ultimately bounded (SGUUB) because the approximation holds only on a certain compact domain; wherefore, the range of the domain must be ensured such that approximation accuracies can be obtained. However, it is impossible that the accurate domain can be chosen precisely in advance, especially in some complicated systems such as multiple input multiple output (MIMO) systems; hence, it is worth to exploit NN or FLS control that can be achieved by global uniformly ultimately bounded (GUUB). In [43], the GUUB stability can be ensured, but output constraint was not considered in the systems. A global adaptive NN control with presetting tracking performance is designed for a class hypersonic flight vehicle in [44]. A switching adaptive NN controller was projected for the GUUB stability of bimanual robot systems in [45], and tailored transient performances can be achieved at the same time. Nevertheless, these global controllers are the main focus on the approximation of NNs to equalize the unknown nonlinearities or dynamic model in systems. From the viewpoint of engineering, FLSs have advantages of high interpretability of rich expert experiences over NNs, so it is important to design a fuzzy adaptive control of the GUUB stability in practical engineering.

Inspired by the above descriptions, we attempt to solve these problems by using FLSs with abundant experiences or languages of experts in this paper. A fuzzy adaptive control based on the BLF technique is proposed for an unknown robot manipulator with time-varying constraints. The stability of GUUB can be guaranteed for the closed-loop system by introducing switching mechanism. The main advantages of this design method are as follows:

(1) A nonzero time-varying parameter is introduced in FLSs, and a fuzzy adaptive controller is designed to get the good tracking performance with time-varying output constraint.

(2) All the signals can be guaranteed GUUB in the closed-loop robot manipulator.

2. System Descriptions and Preliminaries

2.1. Descriptions and Assumptions of Robot Manipulators. The n-link robot manipulator is considered as the following dynamical equation:

$$\mathbf{M}(q)\ddot{\mathbf{q}} + \mathbf{C}(q,\dot{q})\dot{q} + \mathbf{G}(q) = \tau(t) - \mathbf{J}^T(q)f(t), \tag{1}$$

where $q \in R^{n\times 1}$ denotes the joint angular positions, $\dot{q} \in R^{n\times 1}$ is the velocity, and $\ddot{\mathbf{q}} \in R^{n\times 1}$ denotes acceleration vectors; $\mathbf{M}(q) \in R^{n\times n}$ is a symmetric positive known inertia matrix, $\mathbf{C}(q,\dot{q}) \in R^{n\times n}$ denotes the centripetal and Coriolis force vector, $\mathbf{G}(q) \in R^{n\times 1}$ denotes the gravity vector, $\tau(t) \in R^{n\times 1}$ represents the input torque, $\mathbf{J}(q)$ is the unknown reversible Jacobian matrix, and $f(t)$ denotes the constrained force, which satisfies $\|f(t)\| \le \bar{f}$ for $t > 0$, $\bar{f} > 0$ is a known constant.

In this paper, we assume the position of system (1) to be constrained in a time-varying compact set as

$$\underline{h}_c h(t) \le \mathrm{q} \le \bar{h}_c(t), \quad \forall t \ge 0, \tag{2}$$

where $\underline{h}_c(t) = [\underline{h}_{c_1}, \underline{h}_{c_2}, \dots, \underline{h}_{c_n}]^T$ and $\bar{h}_c(t) = [\bar{h}_{c_1}(t), \bar{h}_{c_2}(t), \dots, \bar{h}_{c_n}(t)]^T$ with $h_{c_i}(t) > \underline{h}_{c_i}(t), \forall t \in R_+, i = 1, \dots, n$.

If $q = x_1 = [x_{11}, x_{12}, \dots, x_{1n}]^T$ and $\dot{q} = x_2 = [x_{21}, x_{22}, \dots, x_{2n}]^T$, then the dynamical system (1) can be transformed into following dynamical equation:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= M^{-1}(x_1)\left[\tau - J^T(x_1)f - C(x_1,x_2)x_2 - G(x_1)\right], \\ y &= x_1. \end{aligned} \tag{3}$$

For a given reference signal vector $\mathbf{y}_d = [y_{d_1}, y_{d_2}, \dots, y_{d_n}]^T$, the control aim is to design a fuzzy adaptive controller such that the output $\mathbf{y} = x_1 = [q_1, q_2, \dots, q_n]^T$ tracks this ideal reference signal vector with small errors, and all the signals in the closed-loop robot manipulators (1) are all be bounded. Meanwhile, the time-varying constrains must be guaranteed without damage.

Assumption 1. Unknown function vector $\Delta(\mathbf{X}) = [\Delta_1(X), \dots, \Delta_n(X)]^T$ on the compact set U and Δ_i satisfies the

Lipschitz condition with coefficient l_i which satisfies $|\Delta_i(\mathbf{X}_1) - \Delta_i(X_2)| \le l_i \|X_1 - X_2\|$.

Assumption 2 [11]. There exist constants $\underline{H}_{cij}$ and $\bar{H}_{cij}$ satisfying that $|\bar{h}_{ci}^{(j)}| \le \bar{H}_{cij}$ and $|\underline{h}_{ci}^{(j)}| \ge \underline{H}_{cij}$, $j = 0, 1, \ldots, n, \forall t > 0$.

Assumption 3 [11]. There exist two function vectors $\bar{\mathbf{X}}_0(t) < \bar{h}_c$ and $\underline{\mathbf{X}}_0 > \underline{h}_c, \forall t > 0$ and exist positive constants X_i which satisfies $|y_d^{(i)}| \le X_i$ and $\underline{\mathbf{X}}_0(t) \le y_d(t) \le \bar{\mathbf{X}}_0(t)$.

Define

$$\begin{aligned} h_{a_i}(t) &= y_{d_i}(t) - \underline{h}_{ci}(t), \\ h_{b_i}(t) &= \bar{h}_{ci}(t) - y_{d_i}(t). \end{aligned} \tag{4}$$

If Assumptions 2 and 3 are hold, then there exist some positive constants $\underline{h}_{bi}, \bar{h}_{bi}, \underline{h}_{ai}$, and $\underline{h}_{ai}$, which can make the following inequalities true:

$$\begin{aligned} \underline{h}_{\alpha i}(t) &\le \underline{h}_{\alpha i}(t) \le \bar{h}_{ai}(t), \\ \underline{h}_{bi}(t) &\le \underline{h}_{bi}(t) \le \bar{h}_{bi}(t). \end{aligned} \tag{5}$$

The tracking error vector is defined as $\mathbf{z}_1 = [z_{11}, z_{11}, \ldots, z_{1n}]^T = [x_{11} - y_{d1}, x_{12} - y_{d2}, \ldots, x_{1n} - y_{dn}]^T$ and $\mathbf{z}_2 = [z_{21}, z_{22}, \ldots, z_{2n}]^T = [x_{21} - \beta_{11}, x_{22} - \beta_{12}, \ldots, x_{2n} - \beta_{1n}]^T$. We introduce the following error coordinates that will be used in the procedure of the control design:

$$\begin{aligned} \zeta_{ai} &= \frac{z_{1i}}{h_{ai}}, \\ \zeta_{bi} &= \frac{z_{1_i}}{h_{bi}}, \\ \zeta_i &= p_i(z_{1i})\zeta_{bi} + (1 - p_i(z_{1i}))\zeta_{ai}, \end{aligned} \tag{6}$$

where

$$p_i(z_{1i}) = \begin{cases} 1, & z_{1i} > 0, \\ 0, & z_{1i} \le 0. \end{cases} \tag{7}$$

The following Lemmas 1 and 2 are introduced.

Lemma 1 [11]. *For a given $|\zeta_i| < 1$ and any integer $r > 0$, then $\log(1/(1 - \zeta_i^{2r})) < (\zeta_i^{2r}/(1 - \zeta_i^{2r}))$ is hold.*

Lemma 2 [11]. *If $-h_{ai}(t) < z_{1i}(t) < h_{bi}(t)$, then $|\zeta_i(t)| < 1$ can be obtained.*

2.2. Descriptions of Fuzzy Logic Systems. The following Mamdani type FLS with q fuzzy rules and the kth rule is to be considered:

If x_1 is A_1^k, x_2 is A_2^k, $\cdots$, and x_n is A_n^k, then

$$y = B^k, \quad k = 1, 2, \ldots, q, \tag{8}$$

where A_h^k and B^k denote fuzzy sets. $A_h^k(x_h)$ $(h = 1, 2, \ldots, n)$ is the membership function of x_h. Now, a nonzero time-varying parameter $\rho = \rho(t)$ is introduced in the fuzzy rule (8). According to the defuzzification in [12], the output of the fuzzy logic system (8) can be written as

$$y = \frac{\sum_{k=1}^{q} y^k \prod_{h=1}^{n} A_h^k(x_h/\rho)}{\sum_{k=1}^{q} \prod_{h=1}^{n} A_h^k(x_h/\rho)}, \tag{9}$$

where $y^k = \max_{y^k \in R} \mu_{B^k}(y^k)$. On a given compact set, we know that the FLS (8) can be utilized to approximate any given uncertain continuous function with any degree of accuracy. Therefore, based on this property of universal approximation, Lemma 3 can be easily obtained.

Lemma 3. *If the uncertain continuous nonlinear function $\Delta_i(X)$ satisfies the Lipschitz condition with coefficient l_i and existing FLSs $F_i(X)$ make $\sup_{X \in U} |\Delta_i(X) - F_i(X)| \le \varepsilon_i$, where $U = \{X \mid \|X\| \le \alpha|\rho|\}$ and ε_i is the approximate error, then the following inequality is hold:*

$$\sup_{X \in U} \left| \Delta_i(X) - F_i\left(\frac{X}{\rho}\right) \right| \le l_i \alpha |\rho - 1| + \varepsilon_i. \tag{10}$$

Proof. In terms of $\Delta_i(X)$, it satisfies the Lipschitz condition with coefficient l_i, such that $|\Delta_i(X) - \Delta_i(X/\rho)| \le l_i \|X - (X/\rho)\|$. If $X \in \{X \mid \|X\| \le \alpha|\rho|\}$ is true, then the following result is also true:

$$\begin{aligned} \left| \Delta_i(X) - F_i\left(\frac{X}{\rho}\right) \right| &\le \left| \Delta_i(X) - \Delta_i\left(\frac{X}{\rho}\right) \right| + \left| \Delta_i\left(\frac{X}{\rho}\right) - F_i\left(\frac{X}{\rho}\right) \right| \\ &\le l_i \alpha |\rho - 1| + \varepsilon_i. \end{aligned} \tag{11}$$

This completed the proof for Lemma 1.

Let $F(X) = [F_1(X), \ldots, F_n(X)]^T$; $\sup_{X \in U} \|\Delta(X) - F(X)\| \le \sqrt{\sum_{i=1}^{n} \varepsilon_i^2} \triangleq \varepsilon$ is easily obtain. From Assumption 1, we define $\sup_{X \in U} \|(l_1, \ldots, l_n)\| \le \sqrt{\sum_{i=1}^{n} l_i^2} \triangleq L$. The values of ε and L are all unknown in this paper, so we introduce $\hat{\varepsilon} = \hat{\varepsilon}(t)$ and $\hat{L} = \hat{L}(t)$ to denote the estimation of ε and L, respectively. $\tilde{\varepsilon} = \hat{\varepsilon} - \varepsilon$ and $\tilde{L} = \hat{L} - L$ denote the estimate error.

3. Fuzzy Adaptive Control Design

In this section, the fuzzy adaptive controller is designed based on backstepping technology and the asymmetric BLF.

From, an asymmetric TVBLF in [11], the following is considered:

$$\begin{aligned} V_1 = & \frac{1}{2r} \sum_{i=1}^{n} p_i(z_{1i}) \log \frac{h_{bi}^{2r}(t)}{h_{bi}^{2r}(t) - z_{1i}^{2r}} \\ & + \frac{1}{2r} \sum_{i=1}^{n} [1 - p_i(z_{1i})] \log \frac{h_{ai}^{2r}(t)}{h_{ai}^{2r}(t) - z_{1i}^{2r}}, \end{aligned} \tag{12}$$

where $r \ge 1$ is an integer of differentiability of β_{1i} $(i = 1, 2, \ldots, n)$. We know that V_1 is continuously differentiable on the set $|\zeta_i| < 1$; then

$$\dot{V}_1 = \sum_{i=1}^{n} \frac{p_i \zeta_{bi}^{2r-1}}{h_{bi}\left(1-\zeta_{bi}^{2r}\right)} \left(\dot{z}_{1i} - z_{1i}\frac{\dot{h}_{bi}}{h_{bi}}\right) + \sum_{i=1}^{n} \frac{(1-p_i)\zeta_{ai}^{2r-1}}{h_{ai}\left(1-\zeta_{ai}^{2r}\right)} \left(\dot{z}_{1i} - z_{1i}\frac{\dot{h}_{ai}}{h_{ai}}\right). \tag{13}$$

Since $\dot{z}_{1i} = \dot{x}_{1i} - \dot{y}_{di} = z_{2i} + \beta_{1i} - \dot{y}_{di}$, (13) can be rewritten as

$$\dot{V} = \sum_{i=1}^{n} \frac{p_i \zeta_{bi}^{2r-1}}{h_{bi}\left(1-\zeta_{bi}^{2r}\right)} \left(z_{2i} + \beta_{1i} - \dot{y}_{di} - z_{1i}\frac{\dot{h}_{ai}}{h_{ai}}\right) + \sum_{i=1}^{n} \frac{(1-p_i)\zeta_{ai}^{2r-1}}{h_{ai}\left(1-\zeta_{ai}^{2r}\right)} \left(z_{2i} + \beta_{1i} - \dot{y}_{di} - z_{1i}\frac{\dot{h}_{ai}}{h_{ai}}\right). \tag{14}$$

Choose $\beta_1 = -(K_1 + \tilde{K}_1(t))z_1 + \dot{y}_d$, and

$$K_1 = \begin{bmatrix} k_{11} & 0 & \cdots & 0 \\ 0 & k_{12} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & k_{1n} \end{bmatrix}, \quad \tilde{K}_1 = \begin{bmatrix} \tilde{k}_{11} & 0 & \cdots & 0 \\ 0 & \tilde{k}_{12} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{k}_{1n} \end{bmatrix}, \tag{15}$$

with $\tilde{k}_{1i}(t) = \sqrt{(\dot{h}_{ai}/h_{ai})^2 + (\dot{h}_{ai}/h_{ai})^2 + o_i}$; positive parameters k_{1i} and o_i are to be given suitable positive constants by the designer.

Based on (6), (14) becomes

$$\dot{V}_1 = \sum_{i=1}^{n} \sigma_i z_{1i}^{2r-1} z_{2i} - \sum_{i=1}^{n} \frac{\zeta_i^{2r}}{1-\zeta_i^{2r}} \left[k_{1i} + \tilde{k}_{1i} + p_{1i}\frac{\dot{h}_{bi}}{h_{bi}} + (1-p_{1i})\frac{\dot{h}_{ai}}{h_{ai}}\right], \tag{16}$$

where $\sigma_i = (p_{1i}/(h_{bi}^{2r} - z_{1i}^{2r})) + (1 - p_{1i}/(h_{ai}^{2r} - z_{2i}^{2r}))$, because $\tilde{k}_{1i} + (p_{1i}(\dot{h}_{bi}/h_{bi})) + (1-p_{1i})(\dot{h}_{ai}/h_{ai}) \geq 0$; then we have

$$\dot{V}_1 = -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} + \sum_{i=1}^{n} \sigma_i z_{1i}^{2r-1} z_{2i}. \tag{17}$$

Theorem 1. *Consider the robot system described by (1) under Assumptions 1–3, with the condition of $\|z_2\| > \alpha|\rho|$. The following control scheme design as shown in (18) can make sure that the state vector $\bar{\mathbf{X}} = (x_1^T, x_2^T, \beta^T, \dot{\beta}^T, \tilde{L}, \tilde{\varepsilon})^T$ reaches the sliding model surface s as shown in (19) in limited time period.*

$$\begin{aligned} &\tau = [0, 0, \ldots, 0]_{1\times n}^T, \\ &\dot{\rho} = \frac{1}{\alpha^2\rho}\left(\lambda + \sum_{i=1}^{n} \sigma_i |z_{1i}|^{2r-1} |z_{2i}| + \overline{\Delta}\left\|M^{-1}\right\| \|z_2\|\right), \\ &\dot{\hat{L}} = 0, \\ &\dot{\hat{\varepsilon}} = 0, \end{aligned} \tag{18}$$

where the parameters λ and α are known positive constants.

Proof. Since $\|z_2\| > \alpha|\rho|$ and $\|X\| \geq \|z_2\| \geq \alpha|\rho|$ is satisfied, open control is adopted with this condition; choose the sliding model surface as

$$\begin{aligned} s &= s\left(x_1^T, x_2^T, \beta^T, \dot{\beta}^T, \tilde{L}, \tilde{\varepsilon}\right)^T \\ &= V_1 + \frac{1}{2} z_2^T z_2 - \frac{1}{2}\alpha^2\rho^2 + \frac{1}{2\mu_1}\tilde{L}^2 + \frac{1}{2\theta_1}\tilde{\varepsilon}^2. \end{aligned} \tag{19}$$

Define the positive function $\bar{V} = (1/2)s^2$, and according to (17) and (18), the derivative of $\bar{V}$ can be obtained as

$$\begin{aligned} \dot{\bar{V}} = s\Bigg\{ &-\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} + \sum_{i=1}^{n} \sigma_i z_{1r}^{2r-1} z_{2i} \\ &+ z_2^T\left\{M^{-1}(x_1)\left[\tau - J^T(x_1)f - C(x_1,x_2)x_2 - G(x_1)\right] - \dot{\beta}\right\} \\ &- \alpha^2\rho\dot{\rho} + \mu_1^{-1}\tilde{L}\dot{\tilde{L}} + \theta_1^{-1}\tilde{\varepsilon}\dot{\tilde{\varepsilon}}\Bigg\}. \end{aligned} \tag{20}$$

We denote the function vector $\Delta(\mathbf{X}) = J^T(x_1)f + C(x_1, x_2)x_2 + G(x_1) + M(x_1)\dot{\beta}$ and satisfy Assumption 1; we have

$$\begin{aligned} \dot{\bar{V}} \leq s\Bigg\{ &-\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{\zeta_i^{2r}} + \sum_{i=1}^{n} \sigma_n z_{1n}^{2r-1} z_{2n} + \overline{\Delta}\left\|M^{-1}\right\| \cdot \|z_2\| - \dot{\beta} \\ &- \alpha^2\rho\dot{\rho} + \mu_1^{-1}\tilde{L}\dot{\tilde{L}} + \theta_1^{-1}\tilde{\varepsilon}\dot{\tilde{\varepsilon}}\Bigg\} \leq -s\left(\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} + \lambda\right) < 0. \end{aligned} \tag{21}$$

According to [46], (21) means that Theorem 1 can be guaranteed.

Theorem 2. *If Assumptions 1–3 are hold and $\|z_2\| \leq \alpha|\rho|$ can be satisfied, then the proposed fuzzy adaptive control (22) can make the tracking errors converge to a small zero field. All the signals in the closed-loop system can be ensured to be uniformly ultimately bounded.*

$$\begin{aligned} &\tau = -M(x_1)(K_2 z_2 + \Gamma) + F\left(\frac{X}{\rho}\right), \\ &\dot{\rho} = \frac{1}{2}\gamma_1\rho - \delta_1\alpha\left\|M^{-1}\right\|\left(\hat{L}\alpha|1-\rho| + \hat{\varepsilon}\right)\widetilde{\operatorname{sign}}(\rho), \\ &\dot{\hat{L}} = -\gamma_2\hat{L} + \mu_2\alpha^2|\rho| \cdot |1-\rho| \cdot \left\|M^{-1}\right\|, \\ &\dot{\hat{\varepsilon}} = -\gamma_3\hat{\varepsilon} + \theta_2\alpha|\rho| \cdot \left\|M^{-1}\right\|, \end{aligned} \tag{22}$$

where

$$\begin{aligned}
&K_2 = \operatorname{diag}\{k_{21}, k_{22}, \ldots, k_{2n}\},\\
&\widetilde{\operatorname{sign}}(\rho) = \begin{cases} 1, & \rho > 0,\\ -1, & \rho \le 0,\end{cases}\\
&F\left(\frac{X}{\rho}\right) = \left[F_1\left(\frac{X}{\rho}\right), F_2\left(\frac{X}{\rho}\right), \ldots, F_n\left(\frac{X}{\rho}\right)\right]^T,\\
&\Gamma = \left[\sigma_1 z_{11}^{2r-1} z_{21}, \sigma_2 z_{12}^{2r-1} z_{22}, \ldots \sigma_i z_{1i}^{2r-1} z_{2i}\right]^T.
\end{aligned} \tag{23}$$

The parameters $\gamma_1, \gamma_2, \gamma_3, \delta_1, \mu_2$, and θ_2 are positive constants proposed by the designer.

Proof. Because of $\|z_2\| \le \alpha|\rho|$ and $\|X\| \ge \|z_2\|$, so if $\|X\| > \alpha|\rho|$ is satisfied, the control scheme will go back to Theorem 1. But if $\|X\| > \alpha|\rho|$, we consider the following candidate Lyapunov function:

$$V_2 = V_1 + \frac{1}{2} z_2^T z_2. \tag{24}$$

In differentiation V_2, then

$$\dot{V}_2 = \dot{V}_1 + z_2^T \dot{z}_2. \tag{25}$$

We know $\dot{z}_2 = \dot{x}_2 - \dot{\beta}_1 = M^{-1}(x_1)(\tau - \Delta)$, with $\dot{\beta}_1 = [\dot{\beta}_{11}, \dot{\beta}_{12}, \ldots, \dot{\beta}_{1n}]^T$ and $\dot{\beta}_{1i} = (\partial\beta_{1i}/\partial x_{1i})x_{2i} + \sum_{k=0}^{1} \partial\beta_{1i}/\partial\xi_i^{k+1}(\xi_i = [y_{di}, h_{ai}, h_{bi}]^T)$, so the following inequality is true:

$$\dot{V}_2 = -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} + \sum_{i=1}^{n} \sigma_i z_{1i}^{2r-1} z_{2i} + z_2^T M^{-1}(x_1)(\tau - \Delta). \tag{26}$$

Due to the function vector $\Delta = [\Delta_1, \Delta_2, \ldots \Delta_n]^T$ which is unknown, so the approximation of the fuzzy logic systems (9) can be used to deal with the unknown function; then

$$\begin{aligned}
\dot{V}_2 &\le -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} - z_2^T K_2 z_2 + z_2 M^{-1}(x_1)\left[F\left(\frac{X}{\rho}\right) - \Delta\right]\\
&\le -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} - \sum_{i=1}^{n} z_{2i}k_{2i}z_{2i} + \|z_2\|\left\|M^{-1}\right\| \cdot \left\|F\left(\frac{X}{\rho}\right) - \Delta\right\|\\
&\le -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}} - \sum_{i=1}^{n} z_{2i}k_{2i}z_{2i} + \alpha|\rho| \cdot \left\|M^{-1}\right\|(\alpha L|1-\rho| + \varepsilon).
\end{aligned} \tag{27}$$

Define the candidate Lyapunov function.

$$V_3 = V_2 + \frac{1}{2\delta_1}\rho^2 + \frac{1}{2\mu_2}\tilde{L}^2 + \frac{1}{2\theta_2}\tilde{\varepsilon}^2. \tag{28}$$

Then the derivative of V_3 yields

$$\begin{aligned}
\dot{V}_3 &= \dot{V}_2 + \delta_1^{-1}\rho\dot{\rho} + \mu_2^{-1}\tilde{L}\dot{\hat{L}} + \theta_1^{-1}\tilde{\varepsilon}\dot{\hat{\varepsilon}} \le -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}}\\
&\quad - \sum_{i=1}^{n} z_{2i}k_{2i}z_{2i} + \delta_1^{-1}\rho\dot{\rho} + \alpha|\rho| \cdot \left\|M^{-1}\right\|\left(\alpha\hat{L}|1-\rho| + \hat{\varepsilon}\right)\\
&\quad + \mu_2^{-1}\tilde{L}\dot{\hat{L}} - \alpha^2\tilde{L}|\rho| \cdot |1-\rho| \cdot \left\|M^{-1}\right\|\\
&\quad + \theta_2^{-1}\tilde{\varepsilon}\dot{\hat{\varepsilon}} - \alpha|\rho| \cdot \left\|M^{-1}\right\|\tilde{\varepsilon} = -\sum_{i=1}^{n} \frac{k_{1i}\zeta_i^{2r}}{1-\zeta_i^{2r}}\\
&\quad - \sum_{i=1}^{n} z_{2i}k_{2i}z_{2i} - \frac{\gamma_1}{2\delta_1}\rho^2 - \frac{\gamma_2}{\mu_2}\tilde{L}\hat{L} - \frac{\gamma_3}{\theta_2}\tilde{\varepsilon}\hat{\varepsilon}.
\end{aligned} \tag{29}$$

The following inequality is true:

$$-\frac{\gamma_2}{\mu_2}\tilde{L}\hat{L} = -\frac{\gamma_2}{\mu_2}\tilde{L}^2 - \frac{\gamma_2}{\mu_2}\tilde{L}L \le -\frac{\gamma_2}{2\mu_2}\tilde{L}^2 + \frac{\gamma_2}{2\mu_2}L^2. \tag{30}$$

Similarly,

$$-\frac{\gamma_3}{\theta_2}\tilde{\varepsilon}\hat{\varepsilon} = -\frac{\gamma_3}{\theta_2}\tilde{\varepsilon}^2 - \frac{\gamma_3}{\theta_2}\tilde{\varepsilon}\varepsilon \le -\frac{\gamma_3}{2\theta_2}\tilde{\varepsilon}^2 + \frac{\gamma_3}{2\theta_2}\varepsilon^2. \tag{31}$$

Substituting (30) and (31) into (29), it follows that

$$\begin{aligned}
\dot{V}_3 &= -\sum_{i=1}^{n} k_{1i} \log\frac{1}{1-\zeta_i^{2r}} - \sum_{i=1}^{n} z_{2i}k_{2i}z_{2i} - \frac{\gamma_1}{2\delta_1}\rho^2 - \frac{\gamma_2}{2\mu_2}\tilde{L}^2\\
&\quad - \frac{\gamma_3}{2\theta_2}\tilde{\varepsilon}^2 + \frac{\gamma_2}{2\mu_2}L^2 + \frac{\gamma_3}{2\theta_2}\varepsilon^2
\end{aligned} \tag{32}$$

Denote $\varpi = \min\{2rk_{1i}, 2k_{2i}, (\gamma_1/\delta_1), (\gamma_2/\mu_2), (\gamma_3/\theta_2)\}$ and $\upsilon = (\gamma_2/2\mu_2)L^2 + (\gamma_3/2\theta_2)\varepsilon^2$; inequality (32) becomes

$$\dot{V}_3 \le -\varpi V_3 + \upsilon. \tag{33}$$

Multiplying $e^{\varpi t}$ on both sides in (33), then

$$\frac{d}{dt}\left\{V_3 e^{\varpi t}\right\} \le \upsilon e^{\varpi t}. \tag{34}$$

Integrating both sides of (34) over $[0, t]$, get

$$0 \le V_3 \le \left(V_3 - \frac{\upsilon}{\varpi}\right)e^{-\varpi t} + \frac{\upsilon}{\varpi}. \tag{35}$$

From (12), (24), and (28), we have

$$\frac{1}{2r}\log\frac{1}{1-\zeta_i^{2r}} \le V_3(t) \le \bar{V}_3(0), \tag{36}$$

in which $\bar{V}_3(0) = 1/2r\sum_{i=1}^{n}\log(1/(1-\zeta_i^{2r}(0))) + ((1/2)\|z_2(0)\|^2) + ((1/2\delta_2)\rho^2(0)) + ((1/2\mu_2)\tilde{L}^2(0)) + ((1/2\theta_2)\tilde{\varepsilon}^2(0)) + (\upsilon/\varpi)$. We know that $\zeta_i^{2r} \le 1 - e^{-2r\bar{V}_3(0)}$ and $\zeta_i \le (1 - e^{-2r\bar{V}_3(0)})^{1/2r}$.

Based on (6), then

$$-\underline{Q}_i(t) \le z_{1i}(t) \le \bar{Q}_i(t), \tag{37}$$

Table 1: Fuzzy rules of the FLS $F_1(X)$.

kth rule	x_{11}	x_{12}	x_{21}	x_{22}	Δ_1
1	NB	PB	PS	NS	PB
2	PM	NS	PB	NM	NM
3	NS	PM	NB	PB	PM
4	PB	PM	NS	NB	PS
5	PS	PB	NB	PM	NS
6	NS	PS	PB	PN	NB

Table 2: Fuzzy rules of the FLS $F_2(X)$.

kth rule	x_{11}	x_{12}	x_{21}	x_{22}	Δ_2
1	NB	NM	PS	PB	NB
2	NM	NS	PS	PM	NM
3	PS	NM	PB	NM	NS
4	PM	PB	NS	NB	PS
5	PB	PS	NB	NM	NM
6	NS	PB	NM	NS	PB

where $\underline{Q}_i(t) = h_{ai}(t)(1 - e^{-2r\bar{V}_3(0)})^{1/2r}$ and $\bar{Q}_i(t) = h_{bi}(t)(1 - e^{-2r\bar{V}_3(0)})^{1/2r}$.

From Assumptions 2 and 3, we know that $\underline{h}_c(0) < y(0) < \bar{h}_c(0)$, and according to h_{ai} and h_{bi}, then $-h_{ai}(0) < z_i(0) < h_{bi}(0)$, which is equal to $|\zeta_i(0)| < 1$. Based on Lemma 2, $|\zeta_i(t)| < 1$ can be ensured, and $-h_{ai}(t) < z_{1i}(t) < h_{bi}(t)$ is hold. Because $x_{1i} = z_{1i} + y_{di}$, so it gets

$$y_{di}(t) - h_{ai}(t) < x_{1i}(t) < h_{bi}(t) + y_{di}(t). \tag{38}$$

Finally, $\underline{h}_c(t) \leq y(t) \leq \bar{h}_c(t)$ $(\forall t \geq 0)$, so the output signal can not be violated.

We know that the virtual control β_{1i} is bounded, from (35) and (36); $\|z_2\| \leq (2\bar{V}_3(0))^{1/2}$ obtained. Since $z_2 = x_2 - \beta_1$, then x_2 is also bounded. From the updated law in (22), the parameters ρ, $\widehat{L}$ and $\widehat{\varepsilon}$ are all bounded. This is the proof procedure of Theorem 2.

Based on the analysis of Theorem 1 and Theorem 2, we can draw the following Theorem 3 about global stability.

Theorem 3. *For the robot manipulator (1) with Assumptions 1–3 and with the initial output, $\underline{h}_c(0) < y(0) < \bar{h}_c(0)$. When the tracking run out of the domain $U = \{X \mid \|X\| \leq \alpha|\rho|\}$, the updated laws in control (18) will pull the states back to the sliding surface s, and then the proposed switching controls (18) and (22) can guarantee that all the signals in the closed-loop systems are to be GUUB, and all the tracking errors z_{1i} will went to a small field $\Phi_{z_{1i}} = \{z_{1i} \mid -\underline{Q}_i(t) \leq z_{1i}(t) \leq \bar{Q}_i(t)\}$ in a finite time.*

Remark 1. According to the analysis in Theorem 3, we know that the approximation accuracies only updated the online time-varying parameter in a fuzzy logic system, which broke the limitation of exponential growth with the linguistic variables in traditional fuzzy rules such as [24, 27, 28, 33]. This advantage can make designers focus on his/her energy to convey information from human experience to controller action in a complex environment and neglect the computational burden because of the adaptive laws independent with fuzzy rules.

4. Simulation Example

In order to illustrate the fuzzy adaptive controller design, a robot manipulator in [11] with 2-DOF is considered, and the output variable is $q = [q_1, q_2]^T = [x_{11}, x_{12}]^T$. The dynamic robot system can be written as (1) with

$$\begin{aligned}
M(q) &= \begin{bmatrix} \bar{m}_{11} & \bar{m}_{12} \\ \bar{m}_{21} & \bar{m}_{22} \end{bmatrix}, \\
&\bar{m}_{11} = m_1 l_{r1}^2 + m_2\left(l_1^2 + l_{r2}^2 + 2l_1 l_{r2}\cos(q_2)\right) + I_1 + I_2, \\
&\bar{m}_{12} = \bar{m}_{21} = m_2\left(l_{r2}^2 + l_1 l_{r2}\cos(q_2)\right) + I_2, \\
&\bar{m}_{22} = m_2 l_{r2}^2 + I_2, \\
C(q, \dot{q}) &= \begin{bmatrix} \bar{c}_{11} & \bar{c}_{12} \\ \bar{c}_{21} & \bar{c}_{22} \end{bmatrix}, \\
&\bar{c}_{11} = -m_2 l_1 l_{r2}\dot{q}_2 \sin(q_2), \\
&\bar{c}_{12} = -m_2 l_1 l_{r2}(\dot{q}_1 + \dot{q}_2)\sin(q_2), \\
&\bar{c}_{21} = m_2 l_1 l_{r2}\dot{q}_1 \sin(q_2), \\
&\bar{c}_{22} = 0, \\
G(q) &= [\bar{g}_{11}, \bar{g}_{21}]^T, \\
&\bar{g}_{11} = (m_1 l_{r2} + m_2 l_1) g\cos(q_1) + m_2 l_{r2} g\cos(q_1 + q_2), \\
&\bar{g}_{21} = -m_2 l_{r2} g\cos(q_1 + q_2).
\end{aligned} \tag{39}$$

The Jacobian matrix can be chosen as

$$\begin{aligned}
\mathbf{J}(q) &= \begin{bmatrix} \bar{J}_{11} & \bar{J}_{12} \\ \bar{J}_{21} & \bar{J}_{22} \end{bmatrix}, \\
&\bar{J}_{11} = -(l_1\sin(q_1) + l_2\sin(q_1 + q_2)), \\
&\bar{J}_{12} = -l_2\sin(q_1 + q_2), \\
&\bar{J}_{21} = l_1\cos(q_1) + l_2\cos(q_1 + q_2), \\
&\bar{J}_{22} = l_2\cos(q_1 + q_2).
\end{aligned} \tag{40}$$

We know that the order of the system is $q = 2$. The parameters are given as $m_1 = 2$ kg, $m_2 = 0.85$ kg, $l_{r1} = 0.175$ m, $l_1 = 0.35$ m, $l_{r2} = 0.155$ m, $l_2 = 0.31$ m, $I_1 = 0.06125$ kgm^2, $I_2 = 0.02042$ kgm^2, and $g = 9.8$ m/s^2. The initial state vectors are selected as $\mathbf{x}_1(0) = [0, 2]^T$ and $\mathbf{x}_2(0) = [0, 0]^T$. The reference trajectory was provided as $y_d = [\sin(0.5t), 2\cos(0.5t)]^T$. Initial values of updated laws are given as $\rho(0) = 0.5$, $\widehat{L}(0) = 0.3$, and $\widehat{\varepsilon}(0) = 0.9$, and the parameters in the controller are defined as $\alpha = 200$, $\lambda = 100$,

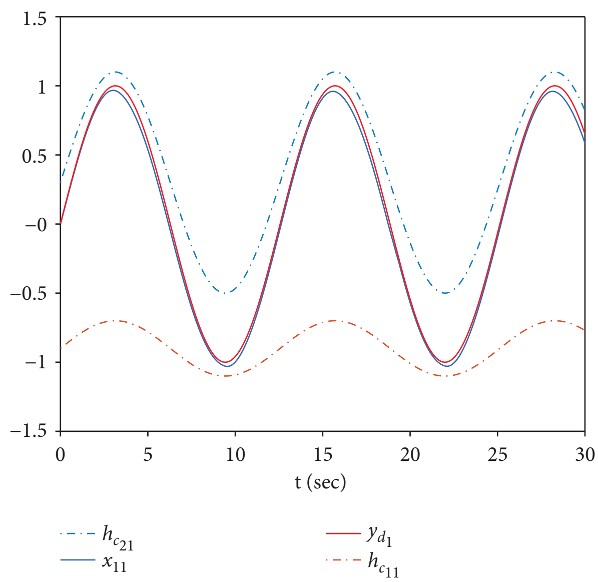

FIGURE 1: The time response of the output x_{11} of Link 1 and ideal reference y_{d_1}.

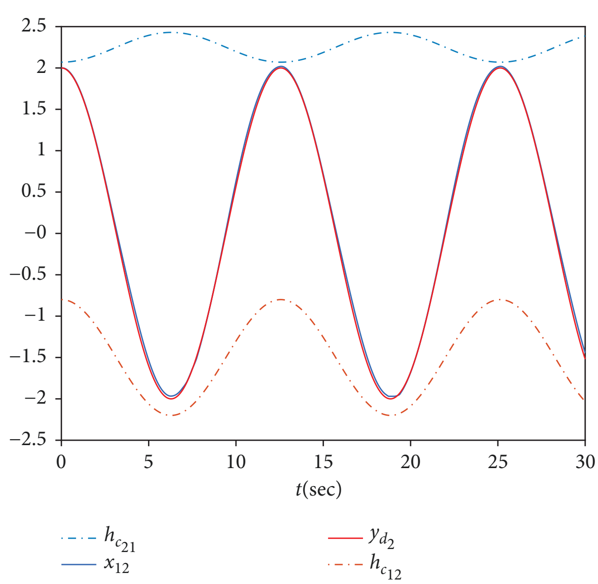

FIGURE 2: The time response of the output x_{12} of Link 2 and ideal reference y_{d_2}.

$\delta_1 = 0.0005$, $o_1 = 0.0002$, $o_1 = 0.0003$, $\gamma_1 = 0.05$, $\gamma_2 = 10$, $\gamma_3 = 40$, $\mu_2 = 0.0005$, and $\theta_2 = 0.0006$.

The constrained force is selected as $f(t) = [1.83 + \sin(t), 1.26 + 2\cos(t)]^T$. We let variable displacement of output constraints as $h_{c1} \le |q| \le h_{c2}$, where $h_{c1} = [h_{c11}, h_{c12}]^T = [0.2\sin(0.5t) - 0.9, 0.7\cos(0.5t) - 1.5]^T$ and $h_{c2} = [h_{c21}, h_{c22}]^T = [0.3 + 0.8\sin(0.5t), -0.18\cos(0.5t) + 2.25]^T$. Define the parameters as $k_{11} = 0.1$, $k_{12} = 0.3$, $k_{21} = 2000$, and $k_{22} = 1500$.

We choose domain $U = U_1 \times U_2 \times U_3 \times U_4 = [-200, 200] \times [-200, 200] \times [-200, 200] \times [-200, 200]$, and fuzzy

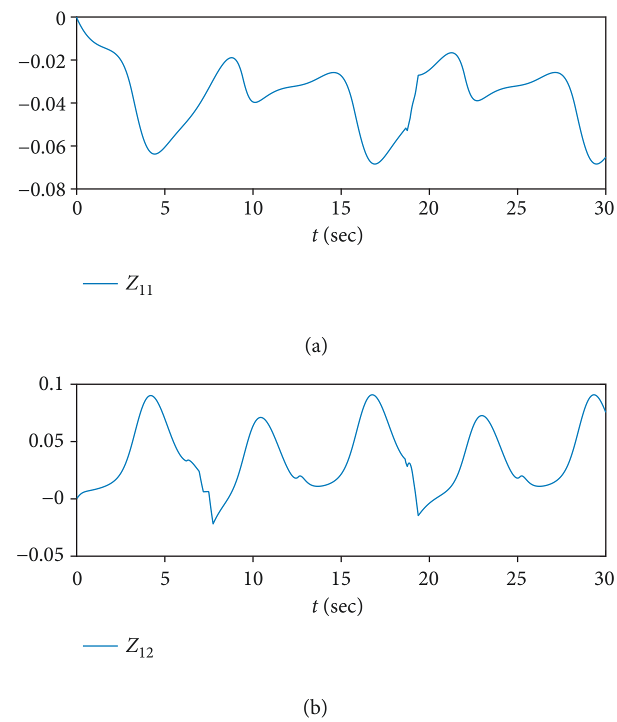

FIGURE 3: The time response of tracking error z_{11} and z_{12}.

linguistic variables selected as *negative big (NB)*, *negative middle (NM)*, *negative small (NS)*, *positive small (PS)*, *positive middle (PM)*, and *positive big (PB)* with the fuzzy membership functions are defined as $(i = 1, 2; j = 1, 2)$:

$$\begin{aligned}
\mu_{NB} &= \frac{1}{1 + e^{\left(x_{ji}+200\right)}},\\
\mu_{NM} &= \frac{1}{1 + e^{\left(x_{ji}+100\right)}},\\
\mu_{NS} &= \frac{1}{1 + e^{\left(x_{ji}+0.1\right)}},\\
\mu_{PS} & \frac{1}{1 + e^{\left(x_{ji}-0.1\right)}},\\
\mu_{PM} &= \frac{1}{1 + e^{\left(x_{ji}-100\right)}},\\
\mu_{PB} &= \frac{1}{1 + e^{\left(x_{ji}-200\right)}}.
\end{aligned} \tag{41}$$

The fuzzy logic system $F_1(X)$ is the six rules in Table 1; $A_{1i}^k \times A_{2i}^k \times A_{3i}^k \times A_{4i}^k \to B_i^k (k = 1, 2, 3, 4, 5, 6)$ can be used to approximate the unknown function $\Delta_1(x_1^x, x_2^T, \beta_1, \dot{\beta}_1)$;

Similarly, the $F_2(X)$ can be constructed in Table 2 by fuzzy rules $\bar{A}_{1i}^k \times \bar{A}_{2i}^k \times \bar{A}_{3i}^k \times \bar{A}_{4i}^k \to \bar{B}_i^k$ instead of the unknown function $\Delta_2(x_1^T, x_2^T, \beta_1, \dot{\beta}_1)$. The simulation results of tracking performance for the robot system are shown as in Figures 1–7.

From the simulation results, Figure 1 shows the output of the first manipulator and the desired trajectory with

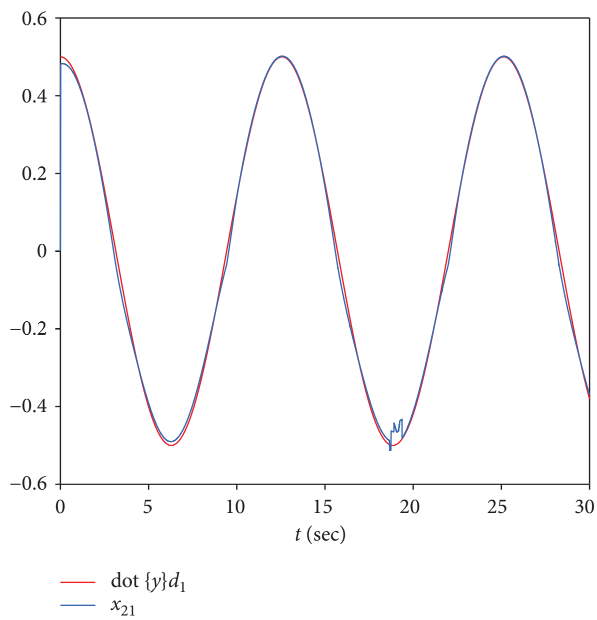

Figure 4: The time response of velocity tracking trajectory of Link 1.

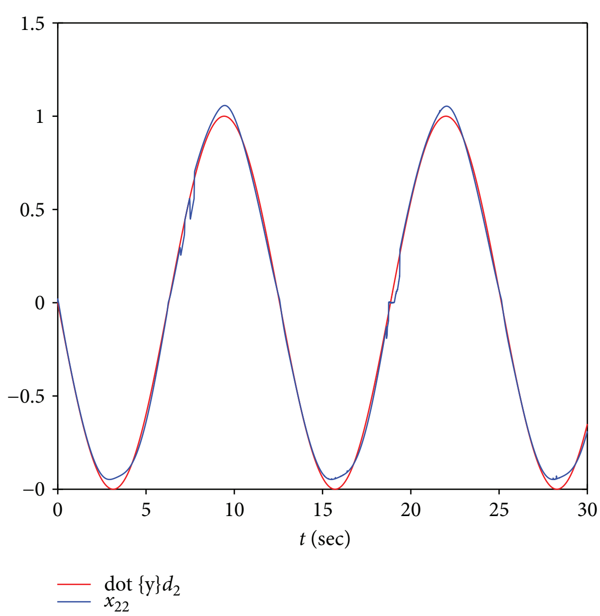

Figure 5: The time response of velocity tracking trajectory of Link 2.

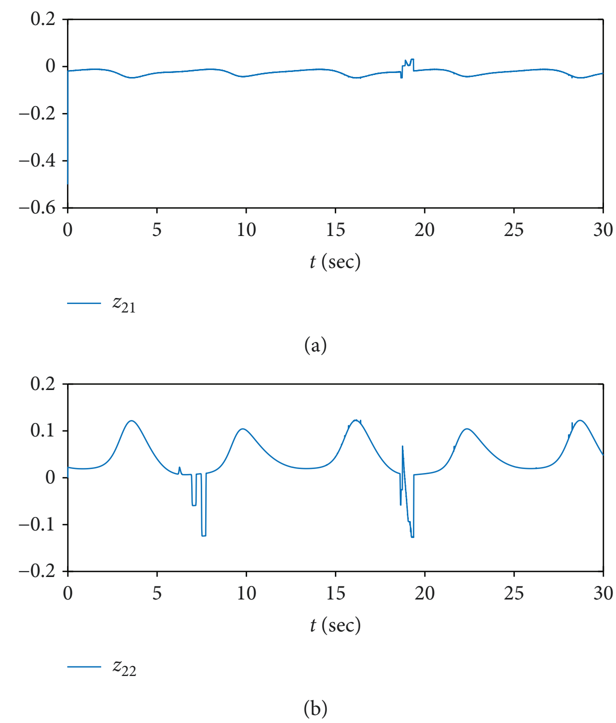

Figure 6: The time response of tracking error z_{21} and z_{22}.

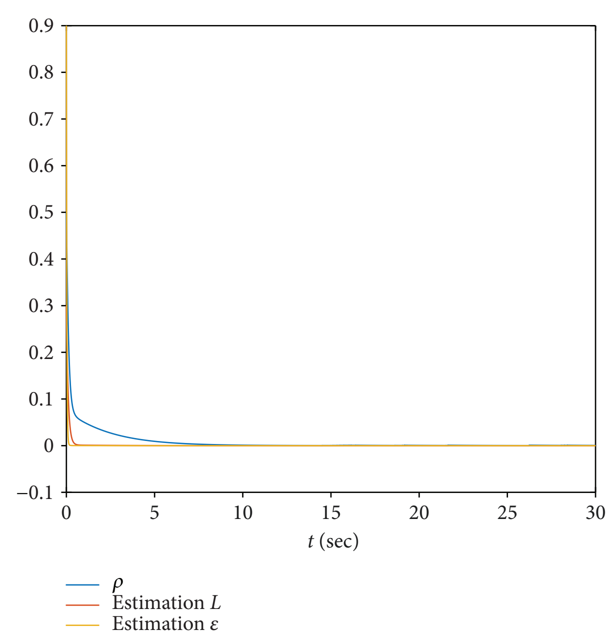

Figure 7: The time response of parameters in controller (18) and (22).

time-varying constraint, and Figure 2 indicates the output of the second manipulator and the reference signal with time-varying constraint. The tracking errors are shown in Figure 3. The time response of velocity of the first manipulator and that of the second manipulator are depicted in Figures 4 and 5, respectively, and the speed of tracking errors is shown in Figure 6. All the adaptive parameters of online time response in controls (18) and (22) are shown in Figure 7, which can be achieved GUUB successfully, and a good tracking performance can be obtained with time-varying constraints from these simulation results.

5. Conclusions

This paper presented a novel fuzzy adaptive switching control based on a time-varying BLF for a robot manipulator with uncertain models; the FLSs combining with the time-varying parameter are used to compensate for the uncertain model system, which extended the traditional fuzzy control that is only emphasized on approximation accuracies and neglected the interpretability of expert language in the procedure of design controllers. By introducing the time-varying parameter in the FLS, global stability can be guaranteed by the switching fuzzy control scheme with neglecting the outside or the inside of the compact domain of the universal approximator.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the financial support from CSC (China Scholarship Council) program (201708615095), the National Natural Science Foundation of China (51405387), the Natural Science Foundation of Shaanxi Province (2016JQ5051), the Shaanxi Province Key Research and Development Plan General Project of Agriculture (2017NY-129), and the Scientific Research Plan Projects of the Education Department of Shaanxi Province (2013JK1073).

References

[1] F. Cuesta, A. Ollero, B. C. Arrue, and R. Braunstingl, "Intelligent control of nonholonomic mobile robots with fuzzy perception," *Fuzzy Sets and Systems*, vol. 134, no. 1, pp. 47–64, 2003.

[2] X. Zhou, X. Liu, A. Jiang, B. Yan, and C. Yang, "Improving video segmentation by fusing depth cues and the visual background extractor (ViBe) algorithm," *Sensors*, vol. 17, no. 5, p. 1177, 2017.

[3] D. McFarlane, S. Sarma, J. L. Chirn, C. Y. Wong, and K. Ashton, "Auto ID systems and intelligent manufacturing control," *Engineering Applications of Artificial Intelligence*, vol. 16, no. 4, pp. 365–376, 2003.

[4] T. Mc Avoy, "Intelligent "control" applications in the process industries," *Annual Reviews in Control*, vol. 26, no. 1, pp. 75–86, 2002.

[5] C. Yang, H. Wu, Z. Li, W. He, N. Wang, and C.-Y. Su, "Mind control of a robotic arm with visual fusion technology," *IEEE Transactions on Industrial Informatics*, p. 1, 2017.

[6] X. Zhou, X. Liu, C. Yang, A. Jiang, and B. Yan, "Multi-channel features spatio-temporal context learning for visual tracking," *IEEE Access*, vol. 5, pp. 12856–12864, 2017.

[7] C. Yang, C. Zeng, P. Liang, Z. Li, R. Li, and C.-Y. Su, "Interface design of a physical human–robot interaction system for human impedance adaptive skill transfer," *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 1, pp. 329–340, 2018.

[8] C. Yang, K. Huang, H. Cheng, Y. Li, and C.-Y. Su, "Haptic identification by elm-controlled uncertain manipulator," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 8, pp. 2398–2409, 2017.

[9] Y. Xu, C. Yang, J. Zhong, N. Wang, and L. Zhao, "Robot teaching by teleoperation based on visual interaction and extreme learning machine," *Neurocomputing*, vol. 275, pp. 2093–2103, 2018.

[10] C. Yang, X. Wang, L. Cheng, and H. Ma, "Neural-learning-based telerobot control with guaranteed performance," *IEEE Transactions on Cybernetics*, vol. 47, no. 10, pp. 3148–3159, 2017.

[11] Y.-J. Liu, S. Lu, and S. Tong, "Neural network controller design for an uncertain robot with time-varying output constraint," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 8, pp. 2060–2068, 2017.

[12] L.-X. Wang and J. M. Mendel, "Fuzzy basis functions, universal approximation, and orthogonal least-squares learning," *IEEE Transactions on Neural Networks*, vol. 3, no. 5, pp. 807–814, 1992.

[13] X. Liu, C. Yang, Z. Chen, M. Wang, and C.-Y. Su, "Neuro-adaptive observer based control of flexible joint robot," *Neurocomputing*, vol. 275, pp. 73–82, 2018.

[14] C. Yang, J. Luo, Y. Pan, Z. Liu, and C.-Y. Su, "Personalized variable gain control with tremor attenuation for robot teleoperation," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1–12, 2017.

[15] C. Yang, X. Wang, Z. Li, Y. Li, and C.-Y. Su, "Teleoperation control based on combination of wave variable and neural networks," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 8, pp. 2125–2136, 2017.

[16] Z. Peng, D. Wang, H. Zhang, and G. Sun, "Distributed neural network control for adaptive synchronization of uncertain dynamical multiagent systems," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 8, pp. 1508–1519, 2014.

[17] W. Wu, S. Zhu, X. Wang, and H. Liu, "Closed-loop dynamic parameter identification of robot manipulators using modified fourier series," *International Journal of Advanced Robotic Systems*, vol. 9, no. 1, p. 29, 2012.

[18] C. Yang, Y. Jiang, W. He, J. Na, Z. Li, and B. Xu, "Adaptive parameter estimation and control design for robot manipulators with finite-time convergence," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 10, pp. 8112–8123, 2018.

[19] F. Wang, B. Chen, C. Lin, J. Zhang, and X. Meng, "Adaptive neural network finite-time output feedback control of quantized nonlinear systems," *IEEE Transactions on Cybernetics*, vol. 48, no. 6, pp. 1839–1848, 2018.

[20] A. Theodorakopoulos and G. A. Rovithakis, "A simplified adaptive neural network prescribed performance controller for uncertain MIMO feedback linearizable systems," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 3, pp. 589–600, 2015.

[21] A. K. Kostarigka and G. A. Rovithakis, "Adaptive dynamic output feedback neural network control of uncertain MIMO nonlinear systems with prescribed performance," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 23, no. 1, pp. 138–149, 2012.

[22] D. Chwa, "Fuzzy adaptive tracking control of wheeled mobile robots with state-dependent kinematic and dynamic disturbances," *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 3, pp. 587–593, 2012.

[23] J. Na, Q. Chen, X. Ren, and Y. Guo, "Adaptive prescribed performance motion control of servo mechanisms with friction compensation," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 1, pp. 486–494, 2014.

[24] E. Kim, "Output feedback tracking control of robot manipulators with model uncertainty via adaptive fuzzy logic," *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 3, pp. 368–378, 2004.

[25] Y. H. Kim and F. L. Lewis, "Neural network output feedback control of robot manipulators," *IEEE Transactions on Robotics and Automation*, vol. 15, no. 2, pp. 301–309, 1999.

[26] S. J. Yoo, J. B. Park, and Y. H. Choi, "Adaptive output feedback control of flexible-joint robots using neural networks: dynamic surface design approach," *IEEE Transactions on Neural Networks*, vol. 19, no. 10, pp. 1712–1726, 2008.

[27] W. He, L. Kong, Y. Dong, Y. Yu, C. Yang, and C. Sun, "Fuzzy tracking control for a class of uncertain MIMO nonlinear systems with state constraints," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1–12, 2017.

[28] W. Gueaieb, F. Karray, and S. Al-Sharhan, "A robust adaptive fuzzy position/force control scheme for cooperative manipulators," *IEEE Transactions on Control Systems Technology*, vol. 11, no. 4, pp. 516–528, 2003.

[29] Q. Zhou, H. Li, and P. Shi, "Decentralized adaptive fuzzy tracking control for robot finger dynamics," *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 3, pp. 501–510, 2015.

[30] J. C. Martínez-Rosas, M. A. Arteaga, and A. M. Castillo-Sánchez, "Decentralized control of cooperative robots without velocity–force measurements," *Automatica*, vol. 42, no. 2, pp. 329–336, 2006.

[31] E. Polak, J. E. Higgins, and D. Q. Mayne, "A barrier function method for minimax problems," *Mathematical Programming*, vol. 54, no. 1–3, pp. 155–176, 1992.

[32] R. Polyak, "Modified barrier functions (theory and methods)," *Mathematical Programming*, vol. 54, no. 1–3, pp. 177–222, 1992.

[33] S.-I. Han and J.-M. Lee, "Adaptive fuzzy backstepping dynamic surface control for output-constrained non-smooth nonlinear dynamic system," *International Journal of Control, Automation and Systems*, vol. 10, no. 4, pp. 684–696, 2012.

[34] Z. Yin, W. He, and C. Yang, "Tracking control of a marine surface vessel with full-state constraints," *International Journal of Systems Science*, vol. 48, no. 3, pp. 535–546, 2017.

[35] Y. Li, T. Li, and X. Jing, "Indirect adaptive fuzzy control for input and output constrained nonlinear systems using a barrier Lyapunov function," *International Journal of Adaptive Control and Signal Processing*, vol. 28, no. 2, pp. 184–199, 2014.

[36] Z.-L. Tang, S. S. Ge, K. P. Tee, and W. He, "Adaptive neural control for an uncertain robotic manipulator with joint space constraints," *International Journal of Control*, vol. 89, no. 7, pp. 1428–1446, 2016.

[37] W. Chang, S. Tong, and Y. Li, "Adaptive fuzzy backstepping output constraint control of flexible manipulator with actuator saturation," *Neural Computing and Applications*, vol. 28, no. S1, pp. 1165–1175, 2017.

[38] Q. Zhou, L. Wang, C. Wu, H. Li, and H. Du, "Adaptive fuzzy control for nonstrict-feedback systems with input saturation and output constraint," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 1, pp. 1–12, 2017.

[39] Y. Li and S. Tong, "Adaptive fuzzy output constrained control design for multi-input multioutput stochastic nonstrict-feedback nonlinear systems," *IEEE Transactions on Cybernetics*, vol. 47, no. 12, pp. 4086–4095, 2017.

[40] Y.-J. Liu and S. Tong, "Barrier Lyapunov Functions-based adaptive control for a class of nonlinear pure-feedback systems with full state constraints," *Automatica*, vol. 64, pp. 70–75, 2016.

[41] Y. J. Liu and S. Tong, "Barrier Lyapunov functions for Nussbaum gain adaptive control of full state constrained nonlinear systems," *Automatica*, vol. 76, pp. 143–152, 2017.

[42] Z. Li, B. Huang, A. Ajoudani, C. Yang, C.-Y. Su, and A. Bicchi, "Asymmetric bimanual control of dual-arm exoskeletons for humancooperative manipulations," *IEEE Transactions on Robotics*, vol. 34, no. 1, pp. 264–271, 2018.

[43] J.-T. Huang, "Global tracking control of strict-feedback systems using neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 23, no. 11, pp. 1714–1725, 2012.

[44] T. Teng, C. Yang, S.-L. Dai, and M. Wang, "Tracking performance and global stability guaranteed neural control of uncertain hypersonic flight vehicle," *International Journal of Advanced Robotic Systems*, vol. 14, no. 1, 2016.

[45] C. Yang, Y. Jiang, Z. Li, W. He, and C.-Y. Su, "Neural control of bimanual robots with guaranteed global stability and motion precision," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 3, pp. 1162–1171, 2017.

[46] J.-J. E. Slotine and W. Li, *Applied Nonlinear Control*, Prentice Hall, Englewood Cliffs, NJ, USA, 1991.


Advances in
Operations Research
Advances in
Decision Sciences
Journal of
Applied Mathematics
The Scientific
World Journal
Journal of
Probability and Statistics
International
Journal of
Mathematics and
Mathematical
Sciences
Hindawi
Submit your manuscripts at
www.hindawi.com
Journal of
Optimization
International Journal of
Engineering
Mathematics
International Journal of
Analysis
Journal of
Complex Analysis
Advances in
Numerical Analysis
Mathematical Problems
in Engineering
International Journal of
Differential Equations
Discrete Dynamics in
Nature and Society
International Journal of
Stochastic Analysis
Journal of
Mathematics
Journal of
Function Spaces
Abstract and
Applied Analysis
Advances in
Mathematical Physics