Event-Triggered Adaptive Asymptotic Tracking Control of Flexible Robotic Manipulators: A Command Filtered Backstepping Method

Tingting Cheng

Shandong Normal University

Ben Niu (✉ niubensdnu@163.com)

Shandong Normal University <https://orcid.org/0000-0002-3680-5594>

Guangju Zhang

Shandong Normal University

Zhenhua Wang

Shandong Normal University

Peiyong Duan

Shandong Normal University

Research Article

Keywords: Adaptive backstepping control, asymptotic tracking control, command-filtered technology, event-triggered control, robotic manipulators

Posted Date: April 12th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-324479/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Event-triggered adaptive asymptotic tracking control of flexible robotic manipulators: A command filtered backstepping method

Tingting Cheng · Ben Niu · Guangju Zhang · Zhenhua Wang · Peiyong Duan

Received: date / Accepted: date

Abstract This paper formulates an event-triggered adaptive asymptotic tracking control scheme for flexible robotic manipulators via command filtered backstepping method. Firstly, in the proposed design algorithm, the unknown nonlinear functions are firstly approximated by using intelligent estimation technique. Then, the “explosion of complexity” problem existing in the traditional backstepping procedure is solved by cleverly applying the command filtered backstepping method. In addition, an event-triggered mechanism is adopted so that the control input is updated irregularly following the occurrence of an event. The advantages of the proposed adaptive design scheme are as follows: (i) the Barbalat’s Lemma is used to asymptotically drive the tracking error to zero; (ii) all the variables in the closed-loop system are bounded; (iii) the utilized event-triggered mechanism reduces the transmission frequency of computer and saves computer resources. Finally, the simulation results of the robotic system are given to illustrate the effectiveness of our design scheme.

Tingting Cheng

School of Information Science and Engineering, Shandong Normal University, Ji’nan, Shandong, 250014, China. E-mail: chengtt2019@163.com

Ben Niu

School of Information Science and Engineering, Shandong Normal University, Ji’nan, Shandong, 250014, China. E-mail: niubensdnu@163.com

Guangju Zhang

School of Chemical Engineering and Materials Science, Shandong Normal University, Ji’nan, Shandong, 250014, China. E-mail: juzi0415@163.com

Zhenhua Wang

School of Information Science and Engineering, Shandong Normal University, Ji’nan, Shandong, 250014, China. E-mail: wzhua111@126.com

Peiyong Duan

School of Information Science and Engineering, Shandong Normal University, Ji’nan, Shandong, 250014, China. E-mail: duanpeiyong@sdsu.edu.cn

Keywords Adaptive backstepping control, asymptotic tracking control, command-filtered technology, event-triggered control, robotic manipulators.

1 Introduction

Over the last few decades, the control problem of robotic manipulators has received outstanding attention, because they can be used to perform useful practical tasks requiring high precision and the performance of robustness in uncertain complex environments. So far, great progress has been made in the research of robotic manipulators and various control strategies have been proposed, see [1–3] and the references therein. However, it is worth pointing out that most of the above results can only guarantee bounded (non-asymptotic) stability of the robotic manipulator systems [4–6]. This means that there is a bounded error between the output of the system and the reference signal when the time tends to infinity. Hence, how to design a control approach to solve the asymptotic output tracking problem for robotic manipulators is a significant research topic. Fortunately, [7] proposed a predictor-based controller for a high-DOF manipulator to converge joint position and velocity errors to zero. Based on the unified kinematics, a unified control method is proposed in [8] to handle the visual tracking control problem of robots with the eye-in-hand or fixed camera configuration and ensure the asymptotical convergence of image position and velocity tracking errors. As a matter of fact, the actual models of robot systems often contain completely unknown uncertainties, but this factor is not taken into account in the above-mentioned results and therefore needs to be solved urgently.

At present, a mainstream research direction for robotic manipulators is to utilize coordinate transformation to transform robotic manipulators into triangular structure models, because the backstepping method can be used for their controller design and stability analysis. As is known to all, the backstepping technique was proposed in [9], and it has become a common tool to construct adaptive controller for the lower-triangular nonlinear systems (and transformed robotic manipulator). For example, [10] proposed a control scheme for robotic manipulators to identify the originally designed virtual control signals in the framework of the backstepping control procedure. [11] presented a control method to train the unknown model dynamics of a manipulator by the traditional backstepping control and obtain the estimated model. However, in the process of backstepping iteration, repeated differentiations of virtual controls increased the computation burden, which is the so-called the problem of “explosion of complexity”. As far as we know, two efficient design methods are proposed to solve the problem of “explosion of complexity” in the backstepping design, one is the dynamic surface control technology and the other is the command filtered technology [12–14]. In addition, some important intelligent estimation techniques [15–24] have been proposed to deal with the completely unknown nonlinearities in nonlinear models. However, these

effective technologies have not been fully applied to the robot systems, which inspires the exploration and research of this paper.

On the other hand, in the traditional time-triggered mechanism, the output of the controller is applied to the system at any time, which will cause the waste of network resources [25–27]. In order to overcome the aforementioned shortcoming, an event-triggered mechanism is proposed, where the control signal is updated at the time instants according to the state trajectory of the closed-loop system. In other words, the state vector follows a condition in a time interval, which is called event condition. Only when the event condition is triggered, the output of the controller is applied to the systems. Until now, event-triggered control has attracted many researchers to explore its application potential due to its remarkable advantages. For example, a control technology called periodic event triggering is proposed in [29], where the continuous evaluation of triggering rule is avoided, and the stability of the event-triggered system is guaranteed. In [30], sliding mode technology combined with event-triggered control is applied to high-order system by the design based on reduced-order model. [31] integrated the event-triggered control into a comprehensive output-feedback mechanism such that the systems allow large uncertainties coupling to unmeasurable states. However, for all we know, few achievements are currently available for robotic manipulator systems via event-triggered control to save communication resources.

Therefore, in this paper we propose an event-triggered adaptive asymptotic tracking control scheme for flexible robotic manipulators by command filtered backstepping method. Different from the traditional time-triggered control strategy, only when the event condition is triggered, the output of the proposed controller can be applied to the system, which greatly reduces the waste of network resources. The contributions of this paper can be summarized as follow: (1) the traditional time-triggered strategy is extended to the event-triggered strategy in this paper. Specifically, the relative threshold strategy is adopted which can adjust the threshold size according to the size of control signal to save the communication resources. (2) By applying some sophisticated mathematical reasoning and famous Barbalat's Lemma, the asymptotic tracking performance of the closed-loop system can be realized. (3) By using the command filtered backstepping technology to avoid repeated derivatives of virtual control, the “explosion of complexity” problem inherent in the traditional backstepping technology is handled.

2 Preliminaries and problem formulation

Consider the dynamic equation of a single-link robotic manipulator coupled with a brushed direct current motor based on a nonrigid joint (Fig.1) as follows:

$$\begin{cases} J_1 \ddot{q}_1 + F_1 \dot{q}_1 + K(q_1 - \frac{q_2}{N}) + mg \cos q_1 = 0, \\ J_2 \ddot{q}_2 + F_2 \dot{q}_2 - \frac{K}{N}(q_1 - \frac{q_2}{N}) = K_t i, \\ Li + Ri + K_b \dot{q}_2 = u, \end{cases} \quad (1)$$

Fig 1. The flexible single-link robotic manipulator.

where J_1 and J_2 are the inertias, q_1 is the angular positions of the link, q_2 is the motor shaft, R and L are the armature resistance and inductance respectively. i denotes the armature current, K denotes the spring constant, K_t is the torque constant, u is the armature voltage, g is the acceleration of gravity, d is the position of the links center of gravity, F_1 and F_2 are the viscous friction constants, K_b is the back-emf constant, M is the link mass, and N is the gear ratio.

Then, by introducing the state variables, $x_1 = q_1$, $x_2 = \dot{q}_1$, $x_3 = q_2$, $x_4 = \dot{q}_2$, $x_5 = i$ and defining $K_t K = J_1 J_2 N L$, the dynamic equation of the system (1) becomes the following non-strict-feedback form:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = \delta_2(x_1, x_2, x_3) + x_3, \\ \dot{x}_3 = x_4, \\ \dot{x}_4 = \delta_4(x_1, x_2, x_3, x_4, x_5) + x_5, \\ \dot{x}_5 = \delta_5(x_1, x_2, x_3, x_4, x_5) + \frac{1}{L}u, \\ y = x_1, \end{cases} \quad (2)$$

where $\delta_2(x_1, x_2, x_3) = -\frac{mgd}{J_1} \cos x_1 - \frac{F_1}{J_1} x_2 - \frac{K}{J_1} x_2 - \frac{K}{J_1} (x_1 - \frac{x_1}{N}) - x_3$, $\delta_4(x_1, x_2, x_3, x_4, x_5) = \frac{K}{J_2 N} (x_1 - \frac{x_3}{N}) - \frac{F_2}{J_2} x_4 + \frac{K_t}{J_2} x_5 - x_5$, $\delta_5(x_1, x_2, x_3, x_4, x_5) = -\frac{R}{L} x_5 - \frac{K_b}{L} x_4$.

Lemma 1: Given $\xi > 0$ and $c \in R$, the following inequality holds:

$$0 \leq |c| - c \tanh\left(\frac{c}{\xi}\right) \leq \kappa \xi, \quad (3)$$

where κ is a constant and $\kappa = 0.2785$.

Lemma 2 [28]: Let $\bar{z}_q = [z_1, z_2, \dots, z_q]^T$ and $S(\bar{z}_q) = [s_1(\bar{z}_q), \dots, s_l(\bar{z}_q)]^T$ be the basis function vector. Then, for any positive integer $m \leq q$, the following inequality holds:

$$\|S(\bar{z}_q)\|^2 \leq \|S(\bar{z}_m)\|^2. \quad (4)$$

Neural networks: To the best of our knowledge, the radial basis function (RBF) neural networks (NNs) are considered as the most effective tool for estimating any continuous function $f(Z) : R^s \rightarrow R$ over a compact set $\Omega_Z \in R^s$ as

$$f(Z) = \theta^T \phi(Z), \quad (5)$$

where $Z \in \Omega_Z \subset R^s$ is input vector, $\theta = [\theta_1, \dots, \theta_l]^T \in R^l$ with $l > 1$ is RBF NNs weight, $\phi(Z) = [\varphi_1(Z), \dots, \varphi_l(Z)]^T$ is the basis function vector. The basis function $\varphi_i(Z)$ is selected in the following form:

$$\varphi_i(Z) = \exp\left[-\frac{(Z - b_i)^T(Z - b_i)}{c^2}\right], i = 1, \dots, l, \quad (6)$$

where $b_i = [b_{i1}, \dots, b_{iq}]$ and c are the center and the width of RBF. In this paper, for given accuracy $\varepsilon > 0$, if the neuron number is sufficiently large, we approximate an unknown continuous function $f(Z)$ via the following form:

$$f(Z) = \theta^{*T} \phi(Z) + \delta(Z), \quad (7)$$

where optimal weight vector θ^* is chosen as

$$\theta^* := \arg \min_{\theta \in R^l} \left\{ \sup_{Z \in \Omega_Z} |f(Z) - \theta^T \phi(Z)| \right\}. \quad (8)$$

3 Neural adaptive controller design

In this section, the command filtered technology will be employed to design an adaptive controller that can guarantee all signals in the closed-loop systems are bounded and asymptotically drive the tracking error to the zero. Firstly, we define the command filter as

$$e_i = x_i - \omega_i, \forall i = 1, \dots, 5, \quad (9)$$

$$\bar{p}_i \dot{\omega}_i + \omega_i = \alpha_i, \omega_i(0) = \alpha_i(0), \forall i = 2, \dots, 5, \quad (10)$$

where e_i and ω_i are the tracking error of the command filter and output of the command filter, respectively. $\omega_1 = y_r$, y_r is the desired trajectory, α_i denotes the virtual controller, $\bar{p}_i$ is a positive constant to be designed.

Then, a 5-step adaptive command filtered backstepping control scheme will be presented. First, we introduce the compensating tracking error signal v_i as

$$v_i = e_i - \xi_i, \forall i = 1, \dots, 5, \quad (11)$$

where ξ_i is the compensating signal of command filter.

Step 1: Choose an appropriate Lyapunov function V_1 as

$$V_1 = \frac{1}{2} v_1^2. \quad (12)$$

Then, we have

$$\dot{V}_1 = v_1(v_2 + \xi_2 + \omega_2 - \alpha_2 + \alpha_2 - \dot{y}_r - \dot{\xi}_1). \quad (13)$$

Choose a compensating signal $\dot{\xi}_1$ as

$$\dot{\xi}_1 = -c_1\xi_1 + \xi_2 + (\omega_2 - \alpha_2) - l_1 \text{sign}(\xi_1), \quad (14)$$

where $c_1 > 0$ and $l_1 > 0$ are known constants.

According to Young's inequality and Lemma 1, we have

$$v_1 l_1 \text{sign}(\xi_1) \leq |v_1| l_1 \leq v_1 \tanh\left(\frac{v_1}{w(t)}\right) l_1 + l_1 \kappa w(t), \quad (15)$$

where κ is a constant and $\kappa = 0.2785$.

Choose a virtual control law α_2 as

$$\alpha_2 = -c_1 e_1 + \dot{y}_r - \tanh\left(\frac{v_1}{w(t)}\right) l_1. \quad (16)$$

By plugging (14) - (16) into (13), we get

$$\dot{V}_1 \leq -c_1 v_1^2 + v_1 v_2 + l_1 \kappa w(t), \quad (17)$$

it should be noted that $w(t)$ is selected such that $\lim_{t \rightarrow \infty} \int_0^t w(\tau) d\tau \leq w_1 \leq +\infty$, where w_1 is a positive constant and $w(t)$ is positive uniform continuous and bounded function.

Step 2: Choose an appropriate Lyapunov function V_2 as

$$V_2 = V_1 + \frac{1}{2}v_2^2 + \frac{1}{2\eta_2}\tilde{\theta}_2^2 + \frac{1}{2\gamma_2}\tilde{\varepsilon}_2^2. \quad (18)$$

Then, we have

$$\begin{aligned} \dot{V}_2 = & \dot{V}_1 + v_2(\delta_2(\bar{x}_3) + v_3 + \xi_3 + \omega_3 - \alpha_3 + \alpha_3 - \dot{\omega}_2 \\ & - \dot{\xi}_2) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 - \frac{1}{\gamma_2}\tilde{\varepsilon}_2\dot{\hat{\varepsilon}}_2. \end{aligned} \quad (19)$$

Choose a compensating signal $\dot{\xi}_2$ as

$$\dot{\xi}_2 = -c_2\xi_2 + \xi_3 + (\omega_3 - \alpha_3) - l_2 \text{sign}(\xi_2) - \xi_1. \quad (20)$$

According to Lemma 1, we have

$$v_2 l_2 \text{sign}(\xi_2) \leq |v_2| l_2 \leq v_2 \tanh\left(\frac{v_2}{w(t)}\right) l_2 + l_2 \kappa w(t). \quad (21)$$

From (7), we have

$$\delta_2(\bar{x}_3) = \theta_2^{*T} \varphi_2(\bar{x}_3) + \varepsilon_2(\bar{x}_3). \quad (22)$$

According to Lemma 1 and Young's inequality, we have

$$\begin{aligned} v_2 \theta_2^{*T} \varphi_2(\bar{x}_3) &\leq |v_2| \frac{1}{2a_2} \theta_2 \varphi_2^T(\bar{x}_3) \varphi_2(\bar{x}_3) + |v_2| a_2 \\ &\leq |v_2| \frac{1}{2a_2} \theta_2 \varphi_2^T(\bar{x}_2) \varphi_2(\bar{x}_2) + |v_2| a_2. \end{aligned} \quad (23)$$

From Lemma 1, we get

$$\begin{aligned} v_2 \theta_2^{*T} \varphi_2(\bar{x}_3) &\leq |v_2| \frac{1}{2a_2} \theta_2 \varphi_2^T(\bar{x}_2) \varphi_2(\bar{x}_2) + |v_2| a_2 \\ &\leq v_2 \tanh\left(\frac{v_2}{w(t)}\right) \frac{1}{2a_2} \theta_2 \varphi_2^T \varphi_2 + a_2 \kappa w(t) \\ &\quad + v_2 \tanh\left(\frac{v_2}{w(t)}\right) a_2 + \frac{1}{2a_2} \theta_2 \varphi_2^T \varphi_2 \kappa w(t), \end{aligned} \quad (24)$$

$$\begin{aligned} v_2 \varepsilon_2(\bar{x}_3) &\leq |v_2| \bar{\varepsilon}_2 \\ &\leq v_2 \tanh\left(\frac{v_2}{w(t)}\right) \bar{\varepsilon}_2 + \bar{\varepsilon}_2 \kappa w(t). \end{aligned} \quad (25)$$

where a_2 is a known constant, $|\varepsilon_2(\bar{x}_3)| \leq \bar{\varepsilon}_2$ and $\bar{\varepsilon}_2$ is a positive constant.

Choose a virtual control law α_3 as

$$\begin{aligned} \alpha_3 &= -c_2 e_2 - e_1 - \tanh\left(\frac{v_2}{w(t)}\right) \frac{1}{2a_2} \hat{\theta}_2 \varphi_2^T \varphi_2 \\ &\quad - \tanh\left(\frac{v_2}{w(t)}\right) a_2 - \tanh\left(\frac{v_2}{w(t)}\right) \hat{\varepsilon}_2 \\ &\quad + \dot{w}_2 - \tanh\left(\frac{v_2}{w(t)}\right) l_2. \end{aligned} \quad (26)$$

By plugging inequalities (20) - (26) into inequality (19), we have

$$\begin{aligned} \dot{V}_2 &\leq \dot{V}_1 - c_2 v_2^2 + v_2 v_3 + v_2 \tanh\left(\frac{v_2}{w(t)}\right) \frac{1}{2a_2} \tilde{\theta}_2 \varphi_2^T \varphi_2 \\ &\quad + v_2 \tanh\left(\frac{v_2}{w(t)}\right) \tilde{\varepsilon}_2 - \frac{1}{\eta_2} \tilde{\theta}_2 \dot{\hat{\theta}}_2 - \frac{1}{\gamma_2} \tilde{\varepsilon}_2 \dot{\hat{\varepsilon}}_2 \\ &\quad + \left(\frac{1}{2a_2} \theta_2 \varphi_2^T \varphi_2 + a_2 + \bar{\varepsilon}_2 + l_2\right) \kappa w(t). \end{aligned} \quad (27)$$

The adaptive laws are selected as

$$\dot{\hat{\theta}}_2 = \frac{\eta_2}{2a_2} v_2 \tanh\left(\frac{v_2}{w(t)}\right) \varphi_2^T \varphi_2 - \eta_2 w(t) \hat{\theta}_2, \quad (28)$$

$$\dot{\hat{\varepsilon}}_2 = \gamma_2 v_2 \tanh\left(\frac{v_2}{w(t)}\right) - \gamma_2 w(t) \hat{\varepsilon}_2. \quad (29)$$

By plugging (28) into (27), we obtain

$$\begin{aligned}\dot{V}_2 \leq & -\sum_{i=1}^2 c_i v_i^2 + v_2 v_3 + \tilde{\varepsilon}_2 w(t) \hat{\varepsilon}_2 + \tilde{\theta}_2 w(t) \hat{\theta}_2 \\ & + \left(\frac{1}{2a_2} \theta_2 \varphi_2^T \varphi_2 + a_2 + \bar{\varepsilon}_2 + \sum_{i=1}^2 l_i\right) \kappa w(t).\end{aligned}\quad (30)$$

Step 3: Choose an appropriate Lyapunov function V_3 as

$$V_3 = V_2 + \frac{1}{2} v_3^2. \quad (31)$$

Then, we have

$$\dot{V}_3 \leq \dot{V}_2 + v_3(v_4 + \xi_4 + \omega_4 - \alpha_4 + \alpha_4 - \dot{\omega}_3 - \dot{\xi}_3). \quad (32)$$

Choose a compensating signal $\dot{\xi}_3$ as

$$\dot{\xi}_3 = -c_3 \xi_3 + \xi_4 + (\omega_4 - \alpha_4) - \xi_2 - l_3 \text{sign}(\xi_3). \quad (33)$$

According to Young's inequality and Lemma 1, we have

$$v_3 l_3 \text{sign}(\xi_3) \leq |v_3| l_3 \leq v_3 \tanh\left(\frac{v_3}{w(t)}\right) l_3 + l_3 \kappa w(t). \quad (34)$$

Choose a virtual control law α_4 as

$$\alpha_4 = -c_3 e_3 + \dot{\omega}_3 - e_2 - \tanh\left(\frac{v_3}{w(t)}\right) l_3. \quad (35)$$

By plugging (33) - (35) into (32), we get

$$\begin{aligned}\dot{V}_3 \leq & -\sum_{i=1}^3 c_i v_i^2 + v_3 v_4 + \tilde{\varepsilon}_2 w(t) \hat{\varepsilon}_2 + \tilde{\theta}_2 w(t) \hat{\theta}_2 \\ & + \left(\frac{1}{2a_2} \theta_2 \varphi_2^T \varphi_2 + a_2 + \bar{\varepsilon}_2 + \sum_{i=1}^3 l_i\right) \kappa w(t).\end{aligned}\quad (36)$$

Step 4: Choose an appropriate Lyapunov function V_4 as

$$V_4 = V_3 + \frac{1}{2} v_4^2 + \frac{1}{2\eta_4} \tilde{\theta}_4^2 + \frac{1}{2\gamma_4} \tilde{\varepsilon}_4^2. \quad (37)$$

Then, we have

$$\begin{aligned}\dot{V}_4 \leq & \dot{V}_3 + v_4(\delta_4(\bar{x}_5) + v_5 + \xi_5 + \omega_5 - \alpha_5 + \alpha_5 - \dot{\omega}_4 \\ & - \dot{\xi}_4) - \frac{1}{\eta_4} \tilde{\theta}_4 \dot{\hat{\theta}}_4 - \frac{1}{\gamma_4} \tilde{\varepsilon}_4 \dot{\hat{\varepsilon}}_4.\end{aligned}\quad (38)$$

Choose a compensating signal $\dot{\xi}_4$ as

$$\dot{\xi}_4 = -c_4\xi_4 + \xi_5 + (\omega_5 - \alpha_5) - l_4 \text{sign}(\xi_4) - \xi_3. \quad (39)$$

According to Lemma 1, we get

$$\begin{aligned} v_4 l_4 \text{sign}(\xi_4) &\leq |v_4| l_4 \\ &\leq v_4 \tanh\left(\frac{v_4}{w(t)}\right) l_4 + l_4 \kappa w(t). \end{aligned} \quad (40)$$

From (7), we have

$$\delta_4(\bar{x}_5) = \theta_4^{*T} \varphi_4(\bar{x}_5) + \varepsilon_4(\bar{x}_5). \quad (41)$$

According to Lemma 1 and Young's inequality, we obtain

$$\begin{aligned} v_4 \theta_4^{*T} \varphi_4(\bar{x}_5) &\leq |v_4| \frac{1}{2a_4} \theta_4 \varphi_4^T(\bar{x}_5) \varphi_4(\bar{x}_5) + |v_4| a_4 \\ &\leq |v_4| \frac{1}{2a_4} \theta_4 \varphi_4^T(\bar{x}_4) \varphi_4(\bar{x}_4) + |v_4| a_4. \end{aligned} \quad (42)$$

From Lemma 1, we get

$$\begin{aligned} v_4 \theta_4^{*T} \varphi_4(\bar{x}_4) &\leq |v_4| \frac{1}{2a_4} \theta_4 \varphi_4^T(\bar{x}_4) \varphi_4(\bar{x}_4) + |v_4| a_4 \\ &\leq v_4 \tanh\left(\frac{v_4}{w(t)}\right) \frac{1}{2a_4} \theta_4 \varphi_4^T \varphi_4 + a_4 \kappa w(t) \\ &\quad + v_4 \tanh\left(\frac{v_4}{w(t)}\right) a_4 + \frac{1}{2a_4} \theta_4 \varphi_4^T \varphi_4 \kappa w(t), \end{aligned} \quad (43)$$

$$v_4 \varepsilon_4(\bar{x}_4) \leq |v_4| \bar{\varepsilon}_4 \leq v_4 \tanh\left(\frac{v_4}{w(t)}\right) \bar{\varepsilon}_4 + \bar{\varepsilon}_4 \kappa w(t), \quad (44)$$

where a_4 is a known constant, $|\varepsilon_4(\bar{x}_4)| \leq \bar{\varepsilon}_4(\bar{x}_4)$ and $\bar{\varepsilon}_4$ is a positive constant.

Choose a virtual control law α_5 as

$$\begin{aligned} \alpha_5 &= -c_4 e_4 - e_3 - \tanh\left(\frac{v_4}{w(t)}\right) \frac{1}{2a_4} \hat{\theta}_4 \varphi_4^T \varphi_4 + \dot{\omega}_4 \\ &\quad - \tanh\left(\frac{v_4}{w(t)}\right) a_4 - \tanh\left(\frac{v_4}{w(t)}\right) \hat{\varepsilon}_4 \\ &\quad - \tanh\left(\frac{v_4}{w(t)}\right) l_4. \end{aligned} \quad (45)$$

By plugging inequalities (39) - (45) into (38), it gets

$$\begin{aligned} \dot{V}_4 &\leq \dot{V}_3 - c_4 v_4^2 + v_4 v_5 + v_4 \tanh\left(\frac{v_4}{w(t)}\right) \frac{1}{2a_4} \tilde{\theta}_4 \varphi_4^T \varphi_4 \\ &\quad + v_4 \tanh\left(\frac{v_4}{w(t)}\right) \tilde{\varepsilon}_4 - \frac{1}{\eta_4} \tilde{\theta}_4 \dot{\theta}_4 - \frac{1}{\gamma_4} \tilde{\varepsilon}_4 \dot{\varepsilon}_4 \\ &\quad + \left(\frac{1}{2a_4} \theta_4 \varphi_4^T \varphi_4 + a_4 + \bar{\varepsilon}_4 + l_4\right) \kappa w(t). \end{aligned} \quad (46)$$

Adaptive laws are selected as

$$\dot{\hat{\theta}}_4 = \frac{\eta_4}{2a_4} v_4 \tanh\left(\frac{v_4}{w(t)}\right) \varphi_4^T \varphi_4 - \eta_4 w(t) \hat{\theta}_4, \quad (47)$$

$$\dot{\hat{\varepsilon}}_4 = \gamma_4 v_4 \tanh\left(\frac{v_4}{w(t)}\right) - \gamma_4 w(t) \hat{\varepsilon}_4. \quad (48)$$

By plugging (47) into (46), we obtain

$$\begin{aligned} \dot{V}_4 \leq & - \sum_{i=1}^4 c_i v_i^2 + \left(\sum_{i=2,4} \frac{1}{2a_i} \theta_i \varphi_i^T \varphi_i + \sum_{i=2,4} a_i + \sum_{i=2,4} \bar{\varepsilon}_i \right. \\ & + \sum_{i=1}^4 l_i \kappa w(t) + v_4 v_5 + \sum_{i=2,4} \tilde{\varepsilon}_i w(t) \hat{\varepsilon}_i \\ & \left. + \sum_{i=2,4} \tilde{\theta}_i w(t) \hat{\theta}_i \right). \end{aligned} \quad (49)$$

Step 5: Choose an appropriate Lyapunov function V_5 as

$$V_5 = V_4 + \frac{1}{2} v_5^2 + \frac{1}{2\eta_5} \tilde{\theta}_5^2 + \frac{1}{2\gamma_5} \tilde{\varepsilon}_5^2. \quad (50)$$

Then, we have

$$\begin{aligned} \dot{V}_5 = & \dot{V}_4 + v_5 (\delta_5(\bar{x}_5) + bu - \dot{\omega}_5 - \dot{\xi}_5) \\ & - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\tilde{\theta}}_5 - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\tilde{\varepsilon}}_5, \end{aligned} \quad (51)$$

where $\frac{1}{L} = b$. Since L is inductance, we get $b > 0$.

Choose a compensating signal $\dot{\xi}_5$ as

$$\dot{\xi}_5 = -c_5 \xi_5 - l_5 \text{sign}(\xi_5) - \xi_4. \quad (52)$$

According to Lemma 1, we have

$$\begin{aligned} v_5 l_5 \text{sign}(\xi_5) & \leq |v_5| l_5 \\ & \leq v_5 \tanh\left(\frac{v_5}{w(t)}\right) l_5 + l_5 \kappa w(t). \end{aligned} \quad (53)$$

From (7), we have

$$\delta_5(\bar{x}_5) = \theta_5^{*T} \varphi_5(\bar{x}_5) + \varepsilon_5(\bar{x}_5). \quad (54)$$

According to Lemma 1 and Young's inequality, we have

$$\begin{aligned}
v_5 \theta_5^{*T} \varphi_5(\bar{x}_5) &\leq |v_5| \frac{1}{2a_5} \theta_5 \varphi_5^T(\bar{x}_5) \varphi_5(\bar{x}_5) + |v_5| a_5 \\
&\leq v_5 \tanh\left(\frac{v_5}{w(t)}\right) \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 \kappa w(t) \\
&\quad + v_5 \tanh\left(\frac{v_5}{w(t)}\right) a_5 + \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 \kappa w(t),
\end{aligned} \tag{55}$$

$$\begin{aligned}
v_5 \varepsilon_5(\bar{x}_5) &\leq |v_5| \bar{\varepsilon}_5 \\
&\leq v_5 \tanh\left(\frac{v_5}{w(t)}\right) \bar{\varepsilon}_5 + \bar{\varepsilon}_5 \kappa w(t).
\end{aligned} \tag{56}$$

where a_5 is a known constant, $|\varepsilon_5(\bar{x}_5)| \leq \bar{\varepsilon}_5(\bar{x}_5)$ and $\bar{\varepsilon}_5$ is a positive constant.

By plugging inequalities (52) - (56) into (51), it can be inferred that

$$\begin{aligned}
\dot{V}_5 &\leq \dot{V}_4 + v_5 \left(\tanh\left(\frac{v_5}{w(t)}\right) a_5 + bu - \dot{\omega}_5 + c_5 \xi_5 + \xi_4 \right. \\
&\quad + \tanh\left(\frac{v_5}{w(t)}\right) \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + \tanh\left(\frac{v_5}{w(t)}\right) \bar{\varepsilon}_5 \\
&\quad + \tanh\left(\frac{v_5}{w(t)}\right) l_5 - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\theta}_5 - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\varepsilon}_5 \\
&\quad \left. + \left(\frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 + \bar{\varepsilon}_5 + l_5 \right) \kappa w(t) \right).
\end{aligned} \tag{57}$$

Then, the event-triggered mechanism is designed as follows

$$u(t) = p(t_k), \forall t \in [t_k, t_{k+1}), t_k > 0, \tag{58}$$

$$t_{k+1} = \inf\{t \in R \mid |d(t)| \geq \delta |u(t)| + m\}, \tag{59}$$

$$d(t) = p(t) - u(t), \tag{60}$$

where $0 < \delta < 1$, $m > 0$, $p(t)$ is the control law to be designed, $d(t)$ is the measurement error.

Remark 1: When $t \in [t_k, t_{k+1})$, the control signal satisfies the equation $u(t) = p(t_k)$. Only when the event-triggered condition is triggered, we will get the control signal $u(t) = p(t_{k+1})$.

From (59), the control law $p(t)$ is designed as follow

$$p(t) = u(t) + \lambda_1(t) \delta u(t) + \lambda_2(t) m, \tag{61}$$

$$u(t) = \frac{p(t) - \lambda_2(t) m}{1 + \lambda_1(t) \delta}, \tag{62}$$

where $-1 \leq \lambda_1(t) \leq 1$, $-1 \leq \lambda_2(t) \leq 1$.

The event-triggered controller is given as follows

$$p(t) = -(1 + \delta) \left(\Delta \tanh \left(\frac{v_5 b \Delta}{w(t)} \right) + m \tanh \left(\frac{v_5 b m}{w(t)} \right) \right), \quad (63)$$

since $\forall g \in R$ and $w > 0$, $-g \tanh \left(\frac{g}{w} \right) \leq 0$, we obtain $v_5 b p \leq 0$.

According to (61) - (63), we get

$$\begin{aligned} \dot{V}_5 &\leq \dot{V}_4 + v_5 \left(\tanh \left(\frac{v_5}{w(t)} \right) \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 - \dot{\omega}_5 + c_5 \xi_5 + \tanh \left(\frac{v_5}{w(t)} \right) \bar{\varepsilon}_5 \right. \\ &\quad + \frac{bp(t) - b\lambda_2(t)m}{1 + \lambda_1(t)\delta} + \xi_4 + \tanh \left(\frac{v_5}{w(t)} \right) l_5 + \tanh \left(\frac{v_5}{w(t)} \right) a_5 \\ &\quad \left. + (a_5 + \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + \bar{\varepsilon}_5 + l_5) \kappa w(t) - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\theta}_5 - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\varepsilon}_5 \right) \\ &\leq \dot{V}_4 + v_5 \left(\tanh \left(\frac{v_5}{w(t)} \right) \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 - \dot{\omega}_5 + c_5 \xi_5 + \tanh \left(\frac{v_5}{w(t)} \right) \bar{\varepsilon}_5 \right. \\ &\quad + \frac{bp(t)}{1 + \delta} + \frac{bm}{1 - \delta} + \xi_4 + \tanh \left(\frac{v_5}{w(t)} \right) l_5 + \tanh \left(\frac{v_5}{w(t)} \right) a_5 \\ &\quad \left. + (\frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 + \bar{\varepsilon}_5 + l_5) \kappa w(t) - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\theta}_5 - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\varepsilon}_5 \right) \\ &\leq \dot{V}_4 + v_5 \left(\tanh \left(\frac{v_5}{w(t)} \right) \frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 - \dot{\omega}_5 + c_5 \xi_5 + \tanh \left(\frac{v_5}{w(t)} \right) \bar{\varepsilon}_5 \right. \\ &\quad + v_5 b \Delta + 0.557 w(t) + \xi_4 + \tanh \left(\frac{v_5}{w(t)} \right) l_5 + \tanh \left(\frac{v_5}{w(t)} \right) a_5 \\ &\quad \left. + (\frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 + \bar{\varepsilon}_5 + l_5) \kappa w(t) - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\theta}_5 - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\varepsilon}_5 \right), \quad (64) \end{aligned}$$

where

$$\begin{aligned} \Delta &= -\frac{1}{b} \left(\tanh \left(\frac{v_5}{w(t)} \right) \frac{1}{2a_5} \hat{\theta}_5 \varphi_5^T \varphi_5 + \tanh \left(\frac{v_5}{w(t)} \right) a_5 + \tanh \left(\frac{v_5}{w(t)} \right) l_5 \right. \\ &\quad \left. + \tanh \left(\frac{v_5}{w(t)} \right) \hat{\varepsilon}_5 - \dot{\omega}_5 + e_4 + c_5 e_5 \right). \quad (65) \end{aligned}$$

Furthermore, we get

$$\begin{aligned} \dot{V}_5 &\leq \dot{V}_4 + v_5 \tanh \left(\frac{v_5}{w(t)} \right) \frac{1}{2a_5} \tilde{\theta}_5 \varphi_5^T \varphi_5 - c_5 v_5^2 + v_5 \tanh \left(\frac{v_5}{w(t)} \right) \tilde{\varepsilon}_5 \\ &\quad - \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \dot{\varepsilon}_5 + (\frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 + \bar{\varepsilon}_5 + l_5 + 0.557) \kappa w(t) - \frac{1}{\eta_5} \tilde{\theta}_5 \dot{\theta}_5 \quad (66) \\ &\leq \dot{V}_4 - c_5 v_5^2 + \frac{1}{\gamma_5} \tilde{\varepsilon}_5 \left(\gamma_5 v_5 \tanh \left(\frac{v_5}{w(t)} \right) - \dot{\varepsilon}_5 \right) + (\frac{1}{2a_5} \theta_5 \varphi_5^T \varphi_5 + a_5 \\ &\quad + \bar{\varepsilon}_5 + l_5 + 0.557) \kappa w(t) + \frac{1}{\eta_5} \tilde{\theta}_5 \left(v_5 \tanh \left(\frac{v_5}{w(t)} \right) \frac{\eta_5}{2a_5} \varphi_5^T \varphi_5 - \dot{\theta}_5 \right). \quad (67) \end{aligned}$$

The adaptive laws are defined as

$$\dot{\hat{\theta}}_5 = v_5 \tanh\left(\frac{v_5}{w(t)}\right) \frac{\eta_5}{2a_5} \varphi_5^T \varphi_5 - \eta_5 w(t) \hat{\theta}_5, \quad (68)$$

$$\dot{\hat{\varepsilon}}_5 = \gamma_5 v_5 \tanh\left(\frac{v_5}{w(t)}\right) - \gamma_5 w(t) \hat{\varepsilon}_5. \quad (69)$$

Combining (66) - (68), we obtain

$$\begin{aligned} \dot{V}_5 \leq & - \sum_{i=1}^5 c_i v_i^2 + \sum_{i=2,4,5} \tilde{\varepsilon}_i w(t) \hat{\varepsilon}_i + \sum_{i=2,4,5} \tilde{\theta}_i w(t) \hat{\theta}_i \\ & + \left(\sum_{i=2,4,5} \frac{1}{2a_i} \theta_i \varphi_i^T \varphi_i + \sum_{i=2,4,5} a_i + \sum_{i=2,4,5} \bar{\varepsilon}_i \right. \\ & \left. + \sum_{i=1}^5 l_i + 0.557 \right) \kappa w(t). \end{aligned} \quad (70)$$

4 Stability analysis

Theorem 1. Consider the flexible single-link robotic manipulator (1), and suppose that the virtual control law (16), (26), (35), (45), adaptive law (28), (47), (68), and the event-triggered mechanism (65) are constructed. Then, the proposed event-triggered control scheme can guarantee: a) the tracking error will converge to zero asymptotically; b) and the variables in all closed-loop systems are bounded.

Proof: According to Young's inequality, we get

$$\begin{aligned} \sum_{i=2,4,5} \tilde{\theta}_i w(t) \hat{\theta}_i & \leq \sum_{i=2,4,5} \frac{1}{2} w(t) \theta_i^2, \\ \sum_{i=2,4,5} \tilde{\varepsilon}_i w(t) \hat{\varepsilon}_i & \leq \sum_{i=2,4,5} \frac{1}{2} w(t) \bar{\varepsilon}_i^2. \end{aligned} \quad (71)$$

Combining (70) and (71), we obtain

$$\dot{V}_5 \leq - \sum_{i=1}^5 c_i v_i^2 + \sum_{i=2,4,5} \tilde{\varepsilon}_i w(t) \hat{\varepsilon}_i + \sum_{i=2,4,5} \tilde{\theta}_i w(t) \hat{\theta}_i + \phi \kappa w(t). \quad (72)$$

Integrating (72) over $[0, t]$, we have

$$V_5(t) \leq V_5(0) - \int_0^t \sum_{i=1}^5 c_i v_i^2(\omega) d\omega + \phi \int_0^t w(\omega) d\omega, \quad (73)$$

where $\phi = \left(\sum_{i=2,4,5} \frac{1}{2a_i} \theta_i \varphi_i^T \varphi_i + \sum_{i=2,4,5} a_i + \sum_{i=2,4,5} \bar{\varepsilon}_i + \sum_{i=1}^5 l_i + 0.557 \right) \kappa + \sum_{i=2,4,5} \frac{1}{2} \bar{\varepsilon}_i^2 + \sum_{i=2,4,5} \frac{1}{2} \theta_i^2$.

Furthermore, we can get

$$\int_0^t \sum_{i=1}^5 c_i v_i^2(\omega) d\omega \leq V_5(0) + \phi w_1. \quad (74)$$

According to Barbalat lemma, we have

$$\lim_{t \rightarrow \infty} v_1 = 0. \quad (75)$$

To ensure the tracking error asymptotically converges to zero, the convergence of the ξ_i should be considered. Hence, we choose the Lyapunov function V_ξ as follows

$$V_\xi = \sum_{i=1}^5 \frac{1}{2} \xi_i^2, \quad (76)$$

then, the time derivative of V_ξ is

$$\begin{aligned} \dot{V}_\xi &= -c_1 \xi_1^2 + \xi_1(\omega_2 - \alpha_2) + \xi_1 \xi_2 - l_1 \xi_1 \text{sign}(\xi_1) \\ &\quad - c_2 \xi_2^2 + \xi_2(\omega_3 - \alpha_3) + \xi_2 \xi_3 - \xi_2 \xi_1 - l_2 \xi_2 \text{sign}(\xi_2) \\ &\quad - c_3 \xi_3^2 + \xi_3(\omega_4 - \alpha_4) + \xi_3 \xi_4 - \xi_3 \xi_2 - l_3 \xi_3 \text{sign}(\xi_3) \\ &\quad - c_4 \xi_4^2 + \xi_4(\omega_5 - \alpha_5) + \xi_4 \xi_5 - \xi_4 \xi_3 - l_4 \xi_4 \text{sign}(\xi_4) \\ &\quad - c_5 \xi_5^2 - \xi_4 \xi_5 - l_5 \xi_5 \text{sign}(\xi_5) \\ &= -\sum_{i=1}^5 c_i \xi_i^2 + \sum_{i=1}^4 \xi_i(\omega_{i+1} - \alpha_{i+1}) - \sum_{i=1}^5 l_i |\xi_i|. \end{aligned} \quad (77)$$

In [14], the relationship between the output of the command filter and the virtual control is proposed, i.e., $\|\omega_{i+1} - \alpha_{i+1}\| \leq \rho_i$, where ρ_i is a known constant. According to (77), if the suitable l_i is chosen, we can get the following inequality:

$$\begin{aligned} \dot{V}_\xi &\leq -\sum_{i=1}^5 c_i \xi_i^2 + \sum_{i=1}^5 |\xi_i| (l_i - \rho_i) \\ &\leq -B_\xi V_\xi - D_\xi V_\xi^{\frac{1}{2}}, \end{aligned} \quad (78)$$

where $B_\xi = 2 \min \{c_i\}$, $D_\xi = \sqrt{2} \min \{(l_i - \rho_i)\}$ and $l_i > \rho_i$. According to the above discussion and (11), we can get ξ_1 can converge to zero and the tracking error converges to zero asymptotically.

Remark 2: In order to eliminate the Zeno phenomenon, we need to prove that there is a $\bar{t} \geq 0$ such that $\forall k \in \mathbb{Z}^+$, $\{t_{k+1} - t_k\} \geq \bar{t}$. According to $d(t) = p(t) - u(t)$, $\forall t \in [t_k, t_{k+1})$, we have

$$\frac{d}{dt} |d| = \frac{d}{dt} (d * d)^{\frac{1}{2}} = \frac{1}{2} (d * d)^{-\frac{1}{2}} (d * \dot{d} + \dot{d} * d) \leq |\dot{d}| = |\dot{p}|. \quad (79)$$

From (63), since all closed-loop signals have been proved to be bounded, we can find a constant $\sigma > 0$ such that $|\dot{p}| \leq \sigma$. It is worth pointing out that $d(t_k) = 0$ and $\lim_{t \rightarrow t_{k+1}} d(t) = \delta|u(t)| + m$. According to (79), we get the lower bound of $\bar{t}$ must satisfy $\bar{t} \geq \frac{\delta|u(t)|+m}{\sigma}$.

5. Simulation study

Fig 2. The trajectories of y_1 and y_r .

Fig 3. The trajectories of tracking error z_1 .

In this section, in order to show the effectiveness of the proposed controller, we consider the single-link robotic manipulator system (1) in which the parameters are selected as $M = 0.5Kg$, $g = 9.8N/Kg$, $d = 0.03m$, $J_2 = 0.5Kgm^2$, $F_2 = 1.5Nms/rad$, $J_1 = 0.01Kgm^2$, $F_1 = 0.05Nms/rad$,

Fig 4. The trajectories of state variables x_2, x_3 .

Fig 5. The trajectories of state variables x_4, x_5 .

$N = 1, K = 50, K_t = 10Nm/A, R = 1\Omega, L = 2H, K_b = 0.1Nm/A$. The desired trajectory is chosen as $y_r = \sin t$.

The simulation is carried out in the frame of Theorem 1 by Matlab routine. The appropriate parameters are selected as $c_1 = 20, c_2 = 30.5, c_3 = 1, c_4 = 0.01, c_5 = 20, l_1 = 0.02, a_2 = 500, a_4 = 300, a_5 = 900, l_2 = l_3 = l_4 = l_5 = 0.01, \eta_2 = \eta_4 = \eta_5 = 0.5, \gamma_2 = \gamma_4 = \gamma_5 = 1, \bar{p}_2 = 0.006, \bar{p}_3 = \bar{p}_5 = 2, \bar{p}_4 = 1.2$. The initial conditions of the states are chosen as $x_1(0) = 0.8, x_2(0) = 0.1$, and other initial conditions are zero.

The simulation results are shown by Figs. 2-9. Fig. 2 displays the tracking performance. Fig. 3 shows the tracking error. Figs. 4-5 indicate the state variables x_2, x_3, x_4, x_5 . The system adaptive laws are plotted in Figs. 6-7. The actual control input u is plotted in Fig. 8. The interval of triggering events is showed in Fig. 9. It can be concluded that the proposed design scheme can achieve all the variables in closed-loop system are bounded and the tracking error converges to zero asymptotically.

Fig 6. The trajectories of adaptive laws $\hat{\theta}_2, \hat{\theta}_4, \hat{\theta}_5$.

Fig 7. The trajectories of adaptive laws $\hat{\varepsilon}_2, \hat{\varepsilon}_4, \hat{\varepsilon}_5$.

5 Conclusions

This paper has proposed the event-triggered adaptive asymptotic tracking control design for flexible robotic manipulators via command filtered backstepping method. The adaptive controller and event-triggered mechanism have been jointly designed by a systematic approach such that the communication resources are saved. By using the intelligent estimation technique, the unknown nonlinear functions lied in the robotic system have been modeled. The “explosion of complexity” problem existing in the traditional backstepping design has been solved by adopting the command filtered backstepping method. The proposed controller not only ensures all the signals in the closed-loop system are bounded, but also asymptotically drives the tracking error to the zero. Finally, the effectiveness of the proposed design scheme is proved by the simulation results of the robotic manipulator.

Conflicts of Interest

Fig 8. The trajectories of actual control input u .

Fig 9. The trajectories of interval of triggering events.

All the authors declare that there are no potential conflicts of interest and approval of the submission.

Funding

This work was supported in part by the National Natural Science Foundation of China, under Grants 61873151, 61773192, 61773246, and 61803225, Shandong Provincial Natural Science Foundation, China, under Grant ZR2019-MF009, Taishan Scholar Project of Shandong Province of China, under Grant tsqn201909078, and Major Program of Shandong Province Natural Science Foundation, under Grant ZR2018ZB0419.

References

1. Kim YH, Lewis FL, Dawson DM, et al. (2000) Intelligent optimal control of robotic manipulators using neural networks. *Automatica* 36: 1355-1364.
2. Hsu SH, Fu LC. (2006) A fully adaptive decentralized control of robot manipulators. *Automatica* 42: 1761-1767.
3. Yu SH, Yu XH, Shirinzadeh BJ, et al. (2005) Continuous finite-time control for robotic manipulators with terminal sliding mode. *Automatica* 41: 1957-1964.
4. Galicki M. (2016) Finite-time trajectory tracking control in a task space of robotic manipulators. *Automatica* 67: 165-170.
5. Heck D, Saccon A, Wouw NVD, et al. (2016) Guaranteeing stable tracking of hybrid position-force trajectories for a robot manipulator interacting with a stiff environment. *Automatica* 63: 235-247.
6. Kostarigka AK, Doulgeri Z, Rovithakis GA, et al. (2013) Prescribed performance tracking for flexible joint robots with unknown dynamics and variable elasticity. *Automatica* 49: 1137-1147.
7. Bagheri M, Naseradinmousavi P, Krstic M, et al. (2019) Feedback linearization based predictor for time delay control of a high-DOF robot manipulator. *Automatica* DOI: 10.1016/j.automatica.2019.06.037.
8. Liang XW, Wang HS, Liu YH, et al. (2015) A unified design method for adaptive visual tracking control of robots with eye-in-hand/fixed camera configuration. *Automatica* 59: 97-105.
9. Krstic M, Kanellakopoulos I, Kokotovic PV, et al. (1995) Nonlinear and adaptive control design. *New York: Wiley*.
10. Zhou Q, Zhao SY, Li HY, et al. (2019) Adaptive neural network tracking control for robotic manipulators with dead zone. *IEEE Transactions on Neural Networks and Learning Systems* 30: 3611-3620.
11. Guo Q, Zhang Y, Celler BG, et al. (1995) Neural adaptive backstepping control of a robotic manipulator with prescribed performance constraint. *IEEE Transactions on Neural Networks and Learning Systems* 30: 3572-3583.
12. Li YX. (2019) Finite time command filtered adaptive fault tolerant control for a class of uncertain nonlinear systems. *Automatica* 106: 117-123.
13. Shen QK, Shi P. (2015) Distributed command filtered backstepping consensus tracking control of nonlinear multiple-agent systems in strict-feedback form. *Automatica* 56: 120-124.
14. Farrell JA, Polycarpou M, Sharma M, et al. (2009) Command filtered backstepping. *IEEE Transactions on Automatic Control* 54: 1391-1395.
15. Li Y, Li Y, Tong S, et al. (2012) Adaptive fuzzy decentralized output feedback control for stochastic nonlinear large-scale systems. *Neurocomputing* 83: 38-46.
16. Chen B, Lin C, Liu X, et al. (2015) Adaptive fuzzy tracking control for a class of MIMO nonlinear systems in nonstrict-feedback form. *IEEE Transactions on Cybernetics* 45: 2744-2755.
17. Li XM, Zhang B, Li P, et al. (2020) Finite-horizon H^∞ state estimation for periodic neural networks over fading channels. *IEEE Transactions on Neural Networks and Learning Systems* 31: 1450-1460.
18. Niu B, Liu JD, Duan PY, et al. (2019) Reduced-order observerbased adaptive fuzzy tracking control scheme of stochastic switched nonlinear systems. *IEEE Transactions on Systems, Man and Cybernetics: Systems* DOI: 10.1109/TSMC.2019.2943882.
19. Zhou Q, Zhao S, Li H, et al. (2019) Adaptive neural network tracking control for robotic manipulators with dead zone. *IEEE Transactions on Neural Networks and Learning Systems* 30: 3611-3620.
20. Liu YJ, Tong S, Chen CLP, et al. (2013) Adaptive fuzzy control via observer design for uncertain nonlinear systems with unmodeled dynamics. *IEEE Transactions on Fuzzy Systems* 21: 275-288.
21. Wang D, Ha M, Qiao J, et al. (2020) Self-learning optimal regulation for discrete-time nonlinear systems under event-driven formulation. *IEEE Transactions on Automatic Control* 65: 1272-1279.

22. Hong YG, Wang JK, Cheng DZ, et al. Adaptive finite-time control of nonlinear systems with parametric uncertainty. *IEEE Transactions on Automatic Control* 51: 858-862.
23. Kim YH, Lewis FL, Dawson DM, et al. (2000) Intelligent optimal control of robotic manipulators using neural networks. *Automatica* 36: 1355-1364.
24. Huang XQ, Lin W, Yang B, et al. (2005) Global finite-time stabilization of a class of uncertain nonlinear systems. *Automatica* 41: 881-888.
25. Liu YC, Chopra N. (2014) On stability and regulation performance for flexible-joint robots with input/output communication delays. *Automatica* 50: 1698-1705.
26. Wang HL. (2013) Passivity based synchronization for networked robotic systems with uncertain kinematics and dynamics. *Automatica* 49: 755-761.
27. Guo K, Pan YP, Zheng DD, et al. (2020) Composite learning control of robotic systems: a least squares modulated approach. *Automatica* DOI: 10.1016/j.automatica.2019.108612.
28. Sun YM, Chen B, Lin C, et al. (2016) Adaptive neural control for a class of stochastic non-strict-feedback nonlinear systems with time-delay. *Neurocomputing* 241: 750-757.
29. Behera AK, Bandyopadhyay B, Yu XH, et al. (2018) Periodic event-triggered sliding mode control. *Automatica* 96: 61-72.
30. Kumari K, Bandyopadhyay B, Reger J, et al. (2020) Event-triggered sliding mode control for a high-order system via reduced-order model based design. *Automatica* DOI: 10.1016/j.automatica.2020.109163.
31. Li FZ, Liu YG. (2020) Adaptive event-triggered output-feedback controller for uncertain nonlinear systems. *Automatica* DOI: 10.1016/j.automatica.2020.109006.

Figures

Figure 1

The flexible single-link robotic manipulator.

Figure 2

The trajectories of y_1 and y_r .

Figure 3

The trajectories of tracking error z_1 .

Figure 4

The trajectories of state variables x_2, x_3 .

Figure 5

The trajectories of state variables x_4, x_5 .

Figure 6

Please see the Manuscript PDF file for the complete figure caption.

Figure 7

Please see the Manuscript PDF file for the complete figure caption.

Figure 8

The trajectories of actual control input u .

Figure 9

The trajectories of interval of triggering events.