

# A novel event-triggered adaptive tracking control framework for a manipulator with aperiodic neural network estimation

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## Abstract

**Purpose** – The purpose of this study is developing the minimum parameter learning law for the weight updating, which reduces the updating of neural network (NN) weight only at triggering instants and makes a trade-off between the estimation accuracy and triggering frequency such that the computing complexity can be decreased. Besides that, a novel “soft” method is first constructed for the control updating at the triggered instants, to reduce the chattering effect of discontinued renewal of control. Addressing to the proposed control and updating method, a novel dead-zone condition with variable boundary about the triggered control signal is derived to ensure the positivity of adjacent execution intervals.

**Design/methodology/approach** – In this paper, to achieve the motion tracking of manipulator with uncertainty of system dynamics and the communication constraints in the control-execution channel, an adaptive event-triggered controller with NN identification is constructed to improve the transmission efficiency of control on the premise of the guaranteed performance. In the proposed method, the NN with intermittent updating is proposed to perform the uncertain approximation with the saved computation, and the triggered mechanism is constructed to regulate the transportation of the signal in the channel of controller-to-actuator.

**Findings** – According to the impulsive Lyapunov function, it can be proved that all the signals are semi-global uniformly ultimately bounded, and the positivity of adjacent execution intervals is also guaranteed by the proposed method. In addition, the chattering effect of control updating at the jumping instants can be relieved by the proposed “soft” mechanism, such that the control accuracy and stability can be guaranteed. Experiments on the JACO2 real manipulator are carried out to verify the effectiveness of the proposed scheme.

**Originality/value** – To the best of the author’s knowledge, this study is firstly to propose a “soft” method to reduce the chattering effect caused by discontinuous updating. Addressing to the updating method designed above, a novel dead-zone condition with variable threshold and boundary is first constructed to ensure the positivity of execution intervals.

**Keywords** Adaptive event triggered control, Backstepping, Robotic manipulator, Aperiodic estimation, Dead-zone condition, Impulsive system

**Paper type** Research paper

## 1. Introduction

Recently, a growing application of robotic manipulators has catalyzed a variety of tasks being expected from a system with the least consumption of resources as much as possible (Yang *et al.*, 2018; Wu *et al.*, 2017). In particular, digital microprocessors own important applications in almost all modern controller-to-actuator (C-A) of manipulator systems for data processing and system monitoring (Zhang and Wei, 2017). Due to the constrained bandwidth and limited resources of chips at their disposal, the signal transmission delay, packet loss may happen in heavy communication workload (Mostafa *et al.*, 2019; Yu *et al.*, 2019; Sandra, 2020). Based on the above facts, aperiodic control techniques were developed upon because there always exists some redundancy in control signal transmission. A better solution is to reduce the signal transmission and updating to instant when the performance is not guaranteed. Event-triggered control (ETC) enables the

system to be concerned if a predetermined error-related criterion is satisfied (Romain *et al.*, 2014; Chen and Li, 2018; Liu *et al.*, 2020). In this way, the flexible control resource allocation with satisfactory control accuracy can be achieved by designing a proper triggering condition (Zhu, 2020).

Literatures in Tripathy *et al.* (2014), Seungmin *et al.* (2021) have studied event triggered mechanisms with different control methods to achieve the limited control transferring of manipulator systems. For example, Tripathy *et al.* (2014) have discussed the optimal control approach to solve robust stabilization problem for robot manipulators with event-based control law. Baek S *et al.* have proposed a communication efficient event-triggered time-delay control for network manipulator control systems (Seungmin *et al.*, 2021). These experimental results show that, compared with the uniform-interval controller, the communication resources have been greatly reduced. However, the above methods are mainly applicable to systems with determinate dynamic parameters

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and structure. With the increasing complexity of the mechanical structure of robot, some biological heuristic control methods have been investigated for controlling such a system. Chen *et al.* have proposed some muscle-synergies-based neuromuscular control and learning methods, which effectively improve the motion performance of musculoskeletal robots and enlighten the control of complex robotic systems with strong redundancy, coupling and nonlinearity (Chen and Qiao, 2020a, 2020b), whereas these methods need the real-time transmission and updating of signals to guarantee the performance, which may cause the waste of communication and calculation.

On account of the control problem of uncertain nonlinear systems with unmatched conditions, the backstepping method combined with the neural network (or called NN for short) identification has been developed, which causes the exact system information dependence to be removed from the control (He *et al.*, 2017; Kong *et al.*, 2019). In particular, the static NN such as radial basis function neural network (RBFNN) is mostly taken into account in the adaptive feedback control for the uncertain and disturbed nonlinear system due to its rigorous convergence (He and Dong, 2018; Kong *et al.*, 2018; Mei, 2019; Huang and Liu, 2019; Li *et al.*, 2021a, 2021b). Apart from the continuous system, NN identification can also be implemented into ETC (Ma *et al.*, 2019; Wang and Philip, 2020; Zhang *et al.*, 2021; Gao *et al.*, 2021a; Sun *et al.*, 2019; Zhao *et al.*, 2021; Qiu *et al.*, 2021). For example, Gao *et al.* (2021b) have developed the adaptive event-triggered tracking control of a manipulator subjecting to uncertain dynamics and unknown disturbance; Sun *et al.* (2019) have proposed a novel dynamic event-triggered robust tracking control method in the C-A channel for manipulators, and the reduced-order observer was designed to deal with disturbance; aiming at the flexible single-link manipulator system, Zhao *et al.* (2021) have built an adaptive event-triggered boundary control scheme. In Qiu *et al.* (2021), they have studied event-triggered-based adaptive NN tracking control of a robotic manipulator with output constraints and disturbance. It is worth noting that the design of event-sampled adaptive controller with NN to solve system uncertainties is still an open problem because the updating form of NN has an influence on control performance. In the above works of adaptive ETC in the C-A channel, NN's updating is driven by time, which will increase the computational complexity. Addressing this problem, some researchers have developed the aperiodic updating with the principle of minimum parameter learning (MPL) for the event-based control (Gao *et al.*, 2021a; Wang *et al.*, 2018; Liu *et al.*, 2019; Margareta and Safonov, 2008) for details. In these works, the weight of NN updates only when it is needed, namely, at triggering instants, whereas a longer updating interval may degrade the estimation of accuracy; thus, a tradeoff between accuracy and efficiency is demanded for the befitting contraction of updating, and this can be realized through designing the reasonable triggering condition and adaptive law. In Gao *et al.* (2021a), the discrete dynamic ETC with aperiodic network estimation has been developed for the robotic manipulator, to improve the adaptability of control method to the system.

Chattering effect is another problem in implementing ETC into the actual control system. The traditional triggering

control method usually adopts the “judgment-switch” mechanism; that is, when the triggered condition is met, the feedback state of control will directly jump to the current value of the system. Hence, this “hard” switching mechanism leads to a serious discontinuity of system control and may further cause the chattering effect that degrades the control stability (Lee and Utkin, 2007; Zhang *et al.*, 2019). In other words, this discontinuous jumping function enforces the motion of the system state to oscillate near the predefined switch surface determined by the triggered threshold. One important solution to overcome the chattering problem is to use a saturation function or filter to smooth the discontinuous control while the system is near the switch surface in a boundary layer (Hou and Fei, 2019; Balamurugan *et al.*, 2017; Wang *et al.*, 2020). However, to the best of the author's knowledge, no study has considered the chattering problem in triggering systems, which motivates this research. In our proposed framework, a novel filter-like “soft” triggering mechanism is constructed in this paper to realize the relative smooth transition from the original state to the new one. Besides that, the updating step size can be changed through introducing the extra parameter.

This paper mainly focuses on the manipulator system with uncertain dynamics and communication constraints. Through combining the NN approximation and backstepping technique, an adaptive NN control policy is developed to deal with the effect of uncertainty on tracking performance. Here, the congestion in communication networks between the controller and actuator is considered. To alleviate the communication and computing burden, the triggering transmission is introduced into the control execution channel and the updating of the network, which is different from the existing time continuous control method in Huang and Liu (2019) and Li *et al.* (2021a, 2021b), whereas the controller design needs to face the following difficulties and challenges:

- How to design control and aperiodic adaptive law to promote asymptotic stability of tracking and weight estimation error?
- How to construct the appropriate “soft” triggering mechanism and corresponding condition, such that the chattering instability can be reduced with a guaranteed Zeno-free behavior?

Compared with the existing methods, the main contributions and innovations of this paper are as follows:

- To reduce chattering and instability caused by the “hard” switching method in traditional ETC, a novel “soft” triggering mechanism is first constructed in the C-A channel, to achieve the relative smooth transition of the control from the original state to the new one at the triggered instants. In addition, through introducing a parameter  $\beta$ , the updating size could be adjusted for the convergence and stability.
- To decrease the computing complexity, the MPL principles are involved in the derived adaptive controller, where the updating of NN weight is only conducted at triggering instants, which is different from the existing ETC studies in Huang and Liu (2019), Ma *et al.* (2019) and Zhang *et al.* (2021).
- Based on the triggered mechanism and adaptive law proposed above, a novel dead-zone triggered condition

with variable boundary is derived. Different from the existing dead-zone ETC in [Qiu et al. \(2021\)](#), [Gao et al. \(2021a\)](#), [Wang et al. \(2018\)](#) and [Liu et al. \(2019\)](#), the triggering threshold and dead-zone boundary change with the control variable, so as to improve the adaptability of triggering to control performance and ensure the positivity of adjacent execution intervals within the above design.

- Finally, based on the impulse Lyapunov function, semi-global uniformly ultimate boundedness (SGUUB) of all the error signals in the closed-loop system is proved.

Notations.  $I \in \mathbb{R}^{N \times N}$  denotes the identity matrix. In case  $x$  is a scalar,  $|x|$  denotes its absolute value. Given a vector  $\alpha \in \mathbb{R}^{N \times 1}$ ,  $\|\alpha\|$  denotes its 2-norm of  $\alpha$ . For a matrix  $B \in \mathbb{R}^{N \times M}$ ,  $\|B\|_F$  represents the Frobenius norm of  $B$ .  $B^T$  is the transposition of the  $B$ . For a square matrix  $S \in \mathbb{R}^{N \times N}$ ,  $\lambda_{\max}(S)$  and  $\lambda_{\min}(S)$  denote the minimum and maximum eigenvalues of  $S$ , respectively.

## 2. Preliminaries and problem formulation

### 2.1 Lemmas

In this paper, the Lyapunov stability theory of impulsive systems and some inequalities are applied, and the specific contents are listed as follows:

Lemma 1. (The stability of impulsive system) ([Romain et al., 2014](#)) Given a nonlinear impulsive system with the assumption that the jumping only occurs at distinct time instants defined as follows:

$$\begin{aligned} \dot{\zeta} &= f_c(\zeta), \quad \zeta \in \Xi_C \subset \mathbb{R}^m \\ \Delta \zeta &= f_d(\zeta), \quad \zeta \in \Xi_D \subset \mathbb{R}^m \end{aligned} \quad (1)$$

where  $f_c$  and  $f_d$  are the function of the system.  $\Xi_C$  and  $\Xi_D$  represent the time flow and jumping set of the  $n$ -dimensional vector  $\zeta$ , respectively. If there exists a continuously differentiable Lyapunov function  $V(\zeta) : \Xi_C \rightarrow \mathbb{R}^m$  and classic  $K_\infty$  functions  $\alpha(\cdot)$  and  $\beta(\cdot)$  satisfying as:

$$\begin{aligned} \alpha\|\zeta\| &\leq V(\zeta) \leq \beta\|\zeta\|, \quad \zeta \in \Xi_C \\ \frac{\partial V(\zeta)}{\partial \zeta} f_c(\zeta) &< 0, \quad \|\zeta\| > \rho, \quad \zeta \in \Xi_C, \quad \zeta \in \Xi_D \\ \Delta V(\zeta) &= V(\zeta + f_d(\zeta)) - V(\zeta) < 0, \quad \|\zeta\| > \rho, \\ \zeta &\in \Xi_D, \quad \zeta \in \Xi_C \end{aligned} \quad (2)$$

where  $\rho$  is a positive constant such that the boundary can be written as:  $B_{\alpha^{-1}(\beta(\rho))} = \{\rho \in \mathbb{R}^m : \|\rho\| \leq \alpha^{-1}(\beta(\rho))\} \subset \Xi_C$  with  $\rho > \beta(\rho)$ . Supposing another boundary in the discrete domain exists, which can be defined as:  $\psi \Delta \Delta \sup_{\rho \in B_{\alpha^{-1}(\beta(\rho))} \cap \Xi_D} (\zeta + V_d(\zeta))$  exists. Then, the variable  $\zeta$  satisfies the semi-global ultimately bounded with  $\alpha^{-1}(\max\{\beta(\rho), \psi\})$ . Furthermore, as  $t \rightarrow \infty$ , it is satisfied as:  $\limsup_{t \rightarrow \infty} \|\zeta\| \leq \alpha^{-1}(\beta(\rho))$ .

Lemma 2. (Young's inequality) ([He et al., 2017](#); [He and Dong, 2018](#)) For any vectors  $a, b \in \mathbb{R}^n$ , the following inequality holds as:

$$a^T b \leq \frac{\kappa^\eta}{\eta} |a|^\eta + \frac{|b|^\mu}{\mu \kappa^\mu} \quad (3)$$

where  $\kappa$ ,  $\mu$  and  $\eta$  are positive constants, and the latter two variables satisfy that:  $(\mu - 1)(\eta - 1) = 1$ .

Lemma 3 ([He et al., 2017](#); [He and Dong, 2018](#)). For any positive variables  $\varpi$  and scalar  $z$ , the hyperbolic tangent function has the following properties:

$$0 \leq |z| - z^T \tanh\left(\frac{z}{\varpi}\right) \leq 0.2785 \varpi \quad (4)$$

where  $-z^T \tanh\left(\frac{z}{\varpi}\right) \leq 0$ .

Lemma 4 ([He et al., 2017](#); [Kong et al., 2019](#)). Consider a real, symmetric and positive-definite matrix  $Q \in \mathbb{R}^{n \times n}$ . For  $\forall y \in \mathbb{R}^n$ , the minimum and maximum eigenvalues of  $Q$ , denoted by  $\lambda_{\min}$  and  $\lambda_{\max}$ , respectively, satisfy the following inequalities:

$$\lambda_{\min}(Q) \|y\|^2 \leq y^T Q y \leq \lambda_{\max}(Q) \|y\|^2 \quad (5)$$

### 2.2 Dynamics of manipulator

Consider the dynamics of a robotic manipulator system with the dimension of joint space being  $n$  can be described by [He and Dong \(2018\)](#):

$$M_m(q_m) \ddot{q}_m + V_m(q_m, \dot{q}_m) \dot{q}_m + G_m(q_m) + f_{dis}(t) = \Gamma \quad (6)$$

where  $q_m \in \mathbb{R}^{n \times 1}$  is the rotation angle vector of joints.  $M_m(q_m) \in \mathbb{R}^{n \times n}$ ,  $V_m(q_m, \dot{q}_m) \in \mathbb{R}^{n \times n}$  and  $G_m(q_m) \in \mathbb{R}^{n \times 1}$  represent the inertia, Coriolis and gravitational force matrices, respectively.  $f_{dis}(t)$  is the external disturbance.  $\Gamma \in \mathbb{R}^{n \times 1}$  is the applied control torque. Some assumptions are made on the  $M_m(q_m)$ ,  $V_m(q_m, \dot{q}_m)$  and  $f_{dis}$  as follows.

Property 1 ([He and Dong, 2018](#); [Kong et al., 2018](#)).  $M_m(q_m)$  is the symmetric and positive matrix satisfying boundedness. There exists two positive constants  $M_{m1}$  and  $M_{m2}$  with  $M_{m2} \geq M_{m1}$  such that the inequation  $M_{m1}I \leq M_m(q_m) \leq M_{m2}I$  is satisfied. In addition, the matrix  $V_m(q_m, \dot{q}_m)$  is also bounded; namely, there exists a positive value  $V_m$  such that  $\|V(q_m, \dot{q}_m)\| \leq V_m \dot{q}_m$  is satisfied.

Property 2 ([He and Dong, 2018](#); [Kong et al., 2018](#)). The matrix  $\dot{M}_m(q_m) - 2V_m(q_m, \dot{q}_m)$  is skew-symmetric.

Assumption 1 ([Mei, 2019](#)). The external disturbances  $f_{dis}(t)$  is bounded such that  $\|f_{dis}(t)\| \leq f_{d1}$  and  $\|\dot{f}_{dis}(t)\| \leq f_{d2}$ , where  $f_{d1}$  and  $f_{d2}$  are two positive upper bound values.

### 2.3 Function estimation with event-triggered radial basis neural networks

To deal with the uncertain dynamics in the control field, RBFNNs are applied to estimate unknown nonlinear functions, and the approximating capability is written in the following form:

$$f_v = \hat{v}^T \Phi(v) \quad (7)$$

where  $f_v \in \mathbb{R}^n$  is the continuous function whose input is defined in the compact set  $v \in \Omega_v \subset \mathbb{R}^l$ .  $\hat{v} \in \mathbb{R}^{m^l \times n}$  is the estimated weight matrix. The response function vector

$\Phi(v) = [\Phi_1(v), \Phi_2(v), \dots, \Phi_m(v)]$  can be obtained by the gaussian radial basis function as follows:

$$\Phi_i(v) = \exp\left(\frac{-(v - \mu_i)^T(v - \mu_i)}{\sigma_i^2}\right) \quad (8)$$

where  $\mu_i$  and  $\sigma_i$  is the center and width of the gaussian radial basis function. With the expected weight  $\vartheta \in \mathbb{R}^{m' \times n}$ , the nonlinear function  $f_v$  can be written as the NN's fitting with the following form:

$$f_v = \vartheta^T \Phi(v) + \zeta_v \quad (9)$$

where  $\zeta_v \in \mathbb{R}^n$  is the approximation error with continuous variable  $v$ , which is a bounded value satisfying as:  $\|\zeta_v\| \leq \bar{\zeta}_{v,M}$ , where  $\bar{\zeta}_{v,M}$  is a positive constant. Next, the function estimation of the event-sampled NN is illustrated by the following Lemma.

**Lemma 5** (Wang and Philip, 2020; Zhang et al., 2021). Define a discrete monotonically increasing time sequence  $\{t_k\}_{k=0}^\infty$  with  $t_0 = 0$ , and as  $k \rightarrow \infty$ ,  $t_k \rightarrow \infty$ . The sampling points at discrete triggering times are defined as triggered variables, which can be written by  $\tilde{v}(t) = v(t_k)$ ,  $t_k \leq t < t_{k+1}$ . Then,  $\forall \tilde{v} \in \Omega_{\tilde{v}} \subset \mathbb{R}^l$ , such that  $f(v)$  can be reconstructed by the weight  $\hat{\vartheta}$  and activation function  $\Phi(\tilde{v})$  with event sampled input as:

$$f(\tilde{v}) = \hat{\vartheta}^T \Phi(\tilde{v}) + \zeta_{\tilde{v}} \quad (10)$$

where  $\vartheta$  in (10) is the expected matrix with event-sampled network, which can be computed by:

$$\vartheta = \arg \min_{\vartheta \in \mathbb{R}^{m' \times n}} \left[ \sup_{v \in \Omega_v, \tilde{v} \in \Omega_{\tilde{v}}} |f(v) - \hat{f}(\tilde{v} | \vartheta)| \right] \quad (11)$$

where  $\zeta_{\tilde{v}}$  is the event-sampled reconstructed error being defined as:  $\zeta_{\tilde{v}} = \Delta \vartheta^T \Phi(v) - \vartheta^T \Phi(\tilde{v}) + \zeta_v$ .

It can be seen from (10)–(11) that the approximation performance is affected by the inexact sampling input of NN, thus, causing a trade-off between the triggering frequency and the estimation performance. The following assumptions about the estimation error and activation function of the event-triggered NN are made:

**Assumption 2** (Wang and Philip, 2020; Zhang et al., 2021). The approximation error of the event-sampled NN satisfies boundedness as:  $\sup_{v \in \Omega_v, \tilde{v} \in \Omega_{\tilde{v}}} \|\zeta_{\tilde{v}}\| \leq \bar{\zeta}_{\tilde{v},M}$  with the positive constant  $\bar{\zeta}_{\tilde{v},M} > 0$ .

**Assumption 3** (Wang and Philip, 2020; Zhang et al., 2021). Activation function satisfies the boundedness and locally Lipschitz, where  $\|\Phi(\cdot)\| \leq \Phi_{max}$  and  $\|\Phi(a) - \Phi(b)\| \leq L_\Phi \|a - b\|$ ,  $\forall a, b \in \Omega_v$ .  $L_\Phi > 0$  is the Lipschitz constant.

**Remark 1.** Based on the description of Stone–Weierstrass theorem, the continuous NN identification error can be made arbitrary small by selecting the appropriate number of neurons. For the estimation error of event-triggered NN, namely,  $\zeta_{\tilde{v}}$ , it satisfies that:  $\|\zeta_{\tilde{v}}\| \leq \|\vartheta^T \Phi(v)\| + \|\vartheta^T \Phi(\tilde{v})\| + \|\zeta_v\|$  with  $\vartheta$ ,  $\Phi(v)$  and  $\zeta_v$

being the bounded value. As such,  $\|\zeta_{\tilde{v}}\|$  is also a bounded value. Moreover, the gaussian kernel function acting as the activation function has the locally Lipschitz and boundedness. Thus, the above assumptions are reasonable.

### 3. Design of event-triggered control

Consider the model-based control problems without network's estimation. Given that the full state information is available, the generalized tracking errors in joint space are defined as:

$$z_1 = q_m - q_{md} \quad (12)$$

$$z_2 = \dot{q}_m - \alpha_1 \quad (13)$$

where  $q_{md} \in \mathbb{R}^{n \times 1}$  is the desired trajectory of joints, and  $\alpha_1 \in \mathbb{R}^{n \times 1}$  is a virtual control signal, which will be defined as follows:

$$\alpha_1 = \dot{q}_{md} - K_1 z_1 - K_r \tanh(z_1) \|z_2\| \quad (14)$$

where  $K_1 \in \mathbb{R}^{n \times n}$  and  $K_r \in \mathbb{R}^{n \times n}$  are positive diagonal matrix.  $\tanh()$  is the hyperbolic tangent saturation function to reduce the control instability under the effect of the uncertain dynamics and disturbance.

For the convenience of dealing with  $z_1$  and  $z_2$ , it follows from (6), (12), (14) and (13) that:

$$\begin{cases} \dot{z}_1 = z_2 + \alpha_1 - \dot{q}_{md} \\ \dot{z}_2 = M_m^{-1}(q_m) [\Gamma - V_m(q_m, \dot{q}_m) z_2 - V_m(q_m, \dot{q}_m) \alpha_1 \\ - G_m(q_m) - M_m(q_m) \dot{\alpha}_1 - f_{dis}] \end{cases} \quad (15)$$

where  $\dot{\alpha}_1 = \frac{\partial \alpha_1}{\partial q_{md}} \dot{q}_{md} + \frac{\partial \alpha_1}{\partial z_1} \dot{z}_1$ . Let  $\Theta_m = V_m(q_m, \dot{q}_m) \alpha_1 + G_m(q_m) + M_m(q_m) \dot{\alpha}_1$  be the dynamic parameters of the system. According to the model-based control rule, the controller is constructed as follows:

$$\Gamma = -z_1 - K_p z_2 + \Theta_m + f_{dis} \quad (16)$$

where  $K_p \in \mathbb{R}^{n \times n}$  is the positive diagonal matrix.

Actually, the parameters the involving kinetic term  $V_m(q_m, \dot{q}_m) \alpha_1 + G_m(q_m) + M_m(q_m) \dot{\alpha}_1$  and disturbance  $f_{dis}$  is uncertain to the controller. To this end, an RBFNN is applied to estimate it as follows:

$$\vartheta^T \Phi(v) + \zeta_v = \Theta_m + f_{dis} \quad (17)$$

where  $v = [x_1, x_2, \alpha_1, \Gamma] \in \mathbb{R}^n$  is the input of NN.  $\zeta_v$  is the bounded error.

Let  $\hat{\vartheta}$  represent the approximation value of  $\vartheta$ . Then, the adaptive controller with approximate NN estimation can be rewritten as:

$$\Gamma = -z_1 - K_p z_2 + \hat{\vartheta}^T \Phi(v) \quad (18)$$

It could be seen from (18) that the control system only considers the situation that both the controller and NNs are transmitted and updated in a time-continuous manner. To



release more communication resources inside the robot, the event-triggered law is constructed in the C-A channel. In this case, the event-based control signal is switched between two modes: one is state holding during the non-triggered period  $t \in [t_k, t_{k+1})$ , and another is state updating in the jumping phase. According to the traditional ETC, the event-based control torque is defined as:

$$\tilde{\Gamma}(t) = \Gamma(t_k), t \in [t_k, t_{k+1}) \quad (19)$$

$$\tilde{\Gamma}(t^+) = \Gamma(t), t = t_k \quad (20)$$

where the control signal is directly jumping into the latest one at the event time. By using this switching method, the chattering effect will be caused. To alleviate this problem, a novel state updating method is designed as:

$$\tilde{\Gamma}(t^+) = \beta \tilde{\Gamma}(t) + (1 - \beta)(\Gamma(t) - \beta \tilde{\Gamma}(t)) \quad (21)$$

It can be seen from progressive updating formula (21) that the step size of updating  $(1 - \beta)(\Gamma(t) - \beta \tilde{\Gamma}(t))$  can be modulated based on the parameter  $\beta$ .

Actually, through designing different values of  $\beta$ , the updating of control can be transformed into different modes. For  $\beta = 1$ , (21) is equivalent to the state holding, whereas for  $\beta = 0$ , (21) becomes the traditional state “hard” jumping. As such, updating mode allows flexible switching according to the value of  $\beta$ , and the soft triggered mechanism can be constructed as (21) with  $\beta$  being designed by:

$$\begin{cases} 0 \leq \beta < 1, & \text{if event is true} \\ \beta = 1, & \text{if event is false} \end{cases} \quad (22)$$

Based on the event-sampled control value, the controller with event-triggered NN estimation is rewritten as:

$$\Gamma = -z_1 - K_p z_2 + \hat{\vartheta}^T \Phi(\tilde{v}) \quad (23)$$

where  $\tilde{v} = [x_1, x_2, \alpha_1, \tilde{\Gamma}]^T$  is the input of NN, which is composed of the ETC signal.

To determine the event instants, a novel dead-zone condition with event-triggered error is constructed by:

$$e(t) = \Gamma(t) - \tilde{\Gamma}(t), t \in [t_k, t_{k+1}) \quad (24)$$

$$t_{k+1} = t_k + \min \left\{ \delta t > 0 \mid \sup_{\tau \in [t_k, t_k + \delta t)} \gamma_1(e(\tau)) \geq \gamma_2(\Gamma(t)) \right\} \quad (25)$$

where  $\gamma_1(e(t))$  in (25) is the dead-zone functions, which can be defined as:  $\gamma_1(e(t)) = \begin{cases} \|e(t)\|, & \text{if } \|\Gamma(t)\| > B_\Gamma(t) \\ 0, & \text{otherwise} \end{cases}$ .  $\gamma_2(\Gamma(t))$  is the threshold function which is used to transform the triggered control error into the evolution of the control state, so as to further promote the convergence of the system. For this reason,  $B_\Gamma(t)$  is the time-varying boundary of the dead-zone, and its concrete form will be given in the later. When the control quantity is located within the boundary, the performance of the system is considered to meet expectations, and no extra

triggering is needed. Note that the proposed dead-zone condition could reduce the triggering frequency and increase the inter-event period according to the system's performance by using a time-varying boundary.

To make the system convergent without violating the Zeno-free behavior, the condition function and boundary of the dead-zone during the time interval  $t \in [t_k, t_{k+1})$  can be designed as follows:

$$\gamma_2(\Gamma(t)) = \frac{k_s}{(1 + \|\hat{\vartheta}\|L_\Phi)} (\|\Gamma(t)\| + \zeta e^{-\beta t_k}) \quad (26)$$

$$B_\Gamma(t) = \frac{(1 + \|\hat{\vartheta}\|L_\Phi)}{k_s} (\beta \|e(t_k)\| + \beta(1 - \beta)\|\tilde{\Gamma}(t_k)\|) \quad (27)$$

where  $\zeta e^{-t_k}$  is the positive term with  $\zeta$  being a positive constant.  $L_\Phi$  is the Lipschitz coefficient.

With the event-sampled control signal in (19) and the triggered error in (25), the dynamics of  $z_2$  in the updating intervals becomes as follows:

$$\begin{aligned} \dot{z}_2 &= M_m^{-1}(q_m) [\tilde{\Gamma}(t) - V_m(q_m, \dot{q}_m)z_2 - V_m(q_m, \dot{q}_m)\alpha_1 - G_m(q_m) \\ &\quad - M_m(q_m)\dot{\alpha}_1 - f_{dis}] \\ &= M_m^{-1}(q_m) [\Gamma(t) - e(t) - V_m(q_m, \dot{q}_m)z_2 - V_m(q_m, \dot{q}_m)\alpha_1 \\ &\quad - G_m(q_m) - M_m(q_m)\dot{\alpha}_1 - f_{dis}], t \in [t_k, t_{k+1}) \end{aligned} \quad (28)$$

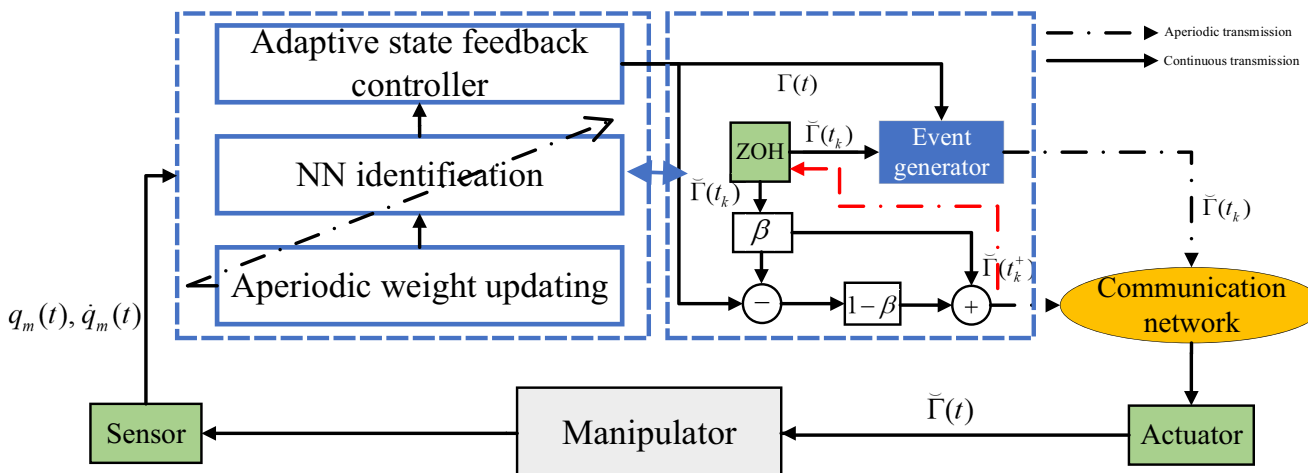
According to (23), the NN with triggering input is used to estimate the system dynamics. According to the characteristics of the triggering system and MPL criteria, an aperiodic adaptive law is designed to update the weights only at the instant when the estimation fails to achieve the desired control performance. In addition, to make a trade-off between the estimation accuracy and triggering efficiency, the adaptive law can be designed as the function of the triggered error as follows:

$$\begin{cases} \dot{\vartheta}_i = 0, & t \in [t_k, t_k) \\ \hat{\vartheta}_i(t^+) = \hat{\vartheta}_i(t) - \rho_1 \Phi(\tilde{v}) \lambda - v_1 \hat{\vartheta}_i(t), & i = 1, 2, \dots, n \\ t = t_k \end{cases} \quad (29)$$

where  $\lambda = \frac{e^T L_s}{\|e\|^2 + c}$  is the feedback signal about the event error with  $L_s$  being the matrix for the matching of dimension.  $c > 0$  is the constant.  $\bar{v}$  and  $\rho_1$  are tuning parameters to modulate the updating.

**Remark 2.** When the state of the system reaches the switching surface composed of trigger threshold, the “soft” mechanism designed by (21) can reduce the chattering by appropriately decreasing the updating size. Taking the norm on both sides of (21), one has:

$$\begin{aligned} \|\tilde{\Gamma}(t^+)\| &\leq \beta \|\tilde{\Gamma}(t)\| + (1 - \beta)\|\Gamma(t)\| + (1 - \beta)\beta \|\tilde{\Gamma}(t)\| \\ &\leq \|\tilde{\Gamma}(t)\| + \|\Gamma(t)\| + \|\tilde{\Gamma}(t)\| \end{aligned} \quad (30)$$



$$\begin{aligned}
\Delta V \hat{\vartheta} &\leq \sum_{i=1}^n \tilde{\vartheta}_i^T(t) v_1 (\vartheta_i(t) - \tilde{\vartheta}_i(t)) + \sum_{i=1}^n \lambda_i \Phi(\tilde{v})^T \rho_1^T \tilde{\vartheta}_i(t) \\
&\quad + \frac{1}{2} \sum_{i=1}^n \lambda_i^T \Phi^T(\tilde{v}) \rho_1^T \rho_1 \Phi(\tilde{v}) \lambda_i \\
&\quad + \sum_{i=1}^n \lambda_i^T \Phi(\tilde{v}) \rho_1^T v_1 (\vartheta_i(t) - \tilde{\vartheta}_i(t)) \\
&\quad + \frac{1}{2} \sum_{i=1}^n (\vartheta_i^T(t) - \tilde{\vartheta}_i^T(t)) v_1^T v_1 (\vartheta_i(t) - \tilde{\vartheta}_i(t)) \\
&= \sum_{i=1}^n \tilde{\vartheta}_i^T(t) v_1 \vartheta_i(t) + \sum_{i=1}^n (1 - v_1) \lambda_i \Phi(\tilde{v})^T \rho_1^T \tilde{\vartheta}_i(t) \\
&\quad - \sum_{i=1}^n \tilde{\vartheta}_i^T(t) v_1 \tilde{\vartheta}_i(t) + \frac{1}{2} \sum_{i=1}^n \lambda_i^T \Phi^T(\tilde{v}) \rho_1^T \rho_1 \Phi(\tilde{v}) \lambda_i \\
&\quad + \sum_{i=1}^n \lambda_i^T \Phi(\tilde{v}) \rho_1^T v_1 \vartheta_i(t) + \frac{1}{2} \sum_{i=1}^n \vartheta_i^T(t) v_1^T v_1 \vartheta_i(t) \\
&\quad - \sum_{i=1}^n \vartheta_i^T(t) v_1^T v_1 \tilde{\vartheta}_i(t) + \frac{1}{2} \sum_{i=1}^n \tilde{\vartheta}_i^T(t) v_1^T v_1 \tilde{\vartheta}_i(t) \\
&\leq \sum_{i=1}^n \lambda_i^T \Phi(\tilde{v}) \rho_1^T v_1 \vartheta_i(t) \\
&\quad - \frac{1}{2} \sum_{i=1}^n \tilde{\vartheta}_i^T(t) (-2v_1^T v_1 + v_1) \tilde{\vartheta}_i(t) \\
&\quad + \frac{1}{2} \sum_{i=1}^n \lambda_i^T \Phi^T(\tilde{v}) \rho_1^T \rho_1 \Phi(\tilde{v}) \lambda_i \\
&\quad - \sum_{i=1}^n (v_1 - 1) \lambda_i \Phi(\tilde{v})^T \rho_1^T \tilde{\vartheta}_i(t) \\
&\quad + \frac{1}{2} \sum_{i=1}^n \vartheta_i^T(t) (2v_1^T v_1 + v_1) \vartheta_i(t)
\end{aligned} \tag{35}$$

Let  $\chi_1 = \frac{1}{2}(-2v_1^T v_1 + v_1)$ ,  $\chi_2 = (v_1 - 1) \lambda_i \Phi(\tilde{v})^T \rho_1^T$ , then, the first and second terms of (35) could be transformed into:

$$\begin{aligned}
&\chi_1 \tilde{\vartheta}_i^T(t) \tilde{\vartheta}_i(t) - \chi_2 \tilde{\vartheta}_i(t) \\
&= -\frac{1}{2} \chi_1 \tilde{\vartheta}_i^T(t) \tilde{\vartheta}_i(t) - \left( \sqrt{\frac{\chi_1}{2}} \tilde{\vartheta}_i(t) - \sqrt{\frac{2}{\chi_1}} \frac{\chi_2}{2} \right)^2 + \frac{\chi_2^2}{2\chi_1}
\end{aligned} \tag{36}$$

Substituting (36) into (35), one has:

$$\begin{aligned}
\Delta V \tilde{\vartheta} &\leq -\sum_{i=1}^n \frac{1}{4} (-2v_1^T v_1 + v_1) \tilde{\vartheta}_i^T(t) \tilde{\vartheta}_i(t) \\
&\quad + \sum_{i=1}^n \frac{[(v_1 - 1) \lambda_i \Phi(\tilde{v})^T \rho_1^T]^2}{(-2v_1^T v_1 + v_1)} \\
&\quad + \frac{1}{2} \sum_{i=1}^n \lambda_i^T \Phi^T(\tilde{v}) \rho_1^T \rho_1 \Phi(\tilde{v}) \lambda_i \\
&\quad + \sum_{i=1}^n \lambda_i^T \Phi(\tilde{v}) \rho_1^T v_1 \vartheta_i(t) + \sum_{i=1}^n \vartheta_i^T(t) (2v_1^T v_1 + v_1) \vartheta_i(t)
\end{aligned}$$

$$\begin{aligned}
&\leq -\sum_{i=1}^n \frac{1}{4} (-2v_1^T v_1 + v_1) \|\tilde{\vartheta}_i(t)\|^2 + \frac{1}{2} \sum_{i=1}^n \|\lambda_i\|^2 \|\Phi(\tilde{v})\|^2 \|\rho_1\|^2 \\
&\quad + \sum_{i=1}^n \|\vartheta_i(t)\|^2 2\|v_1\|^2 + \sum_{i=1}^n \frac{\|v_1 - 1\|^2 \|\lambda_i\|^2 \|\Phi(\tilde{v})\|^2 \|\rho_1\|^2}{\| -2v_1^T v_1 + v_1 \|} \\
&\quad + \sum_{i=1}^n \|\vartheta_i(t)\|^2 \|v_1\| + \sum_{i=1}^n \|\lambda_i\| \|\Phi(\tilde{v})\| \|\rho_1\| \|v_1\| \|\vartheta_i(t)\|
\end{aligned} \tag{37}$$

Let:

$$\begin{aligned}
\chi_n &= \frac{1}{2} \sum_{i=1}^n \|\lambda_i\|^2 \|\Phi(\tilde{v})\|^2 \|\rho_1\|^2 \\
&\quad + \sum_{i=1}^n \frac{\|v_1 - 1\|^2 \|\lambda_i\|^2 \|\Phi(\tilde{v})\|^2 \|\rho_1\|^2}{\| -2v_1^T v_1 + v_1 \|} \\
&\quad + \sum_{i=1}^n \|\vartheta_i(t)\|^2 \|v_1\|^2 + \sum_{i=1}^n \|\lambda_i\| \|\Phi(\tilde{v})\| \|\rho_1\| \|v_1\| \|\vartheta_i(t)\|
\end{aligned}$$

It can be known from (37) that the difference can be expressed as:  $\Delta V \hat{\vartheta} \leq -\frac{1}{2} \chi_1 \sum_{i=1}^n \|\tilde{\vartheta}_i(t)\|^2 + \chi_n$ . When  $0 < v_1 < 0.5$ ,  $\chi_1 > 0$  is ensured to come true. There is no denying that  $\Delta V \hat{\vartheta} < 0$  as long as  $\sum_{i=1}^n \|\tilde{\vartheta}_i(t)\|^2 > \frac{2\chi_n}{\chi_1}$ . According to the stability of impulsive system in Lemma,  $\tilde{\vartheta}$  is ultimately bounded during the updating process of NN, which satisfies as:  $\limsup_{t \rightarrow \infty} \sum_{i=1}^n \|\tilde{\vartheta}_i(t)\| \leq \sqrt{\frac{2\chi_n}{\chi_1}}$ .

In the following theorem, the boundedness of the tracking errors  $z_1$  and  $z_2$ , and all the estimation errors are illustrated.

**Theorem 2.** Consider the dynamic manipulator system under the action of the proposed virtual signal in (14) and event-based transported controller (19)–(23). With the effect of aperiodic adaptive law in (29) by the violation of event condition in (24) and (25). Let Assumptions 1–3 hold. Then, all the tracking errors  $z_1$  and  $z_2$ , as well as the weight estimation error  $\tilde{\vartheta}_i$  remain uniformly ultimately bounded (UUB) as  $t \rightarrow \infty$ .

**Proof.** Construct a new Lyapunov function as follows:

$$V_1 = \frac{1}{2} z_1^T z_1 + \frac{1}{2} z_2^T M_m(q_m) z_2 + \frac{1}{2} \sum_{i=1}^n \tilde{\vartheta}_i^T \tilde{\vartheta}_i \tag{38}$$

where the boundedness of the NN weight estimation error  $\tilde{\vartheta}_i$  has been proved in the previous content. Taking the derivative of  $V_1$  with respect to time for  $t \in [t_k, t_{k+1})$ , introducing the dynamics of  $z_1$  and  $z_2$  with event sampled control torque into (38), one has:

$$\begin{aligned}
\dot{V}_1 &= z_1^T (-K_1 z_1 + z_2 - K_r \tanh(z_1) \|z_2\|) \\
&\quad + z_2^T (\Gamma(t) - e(t) - V_m(q_m, \dot{q}_m) z_2 - \vartheta^T \Phi(v) - \zeta_v) \\
&\leq -z_1^T K_1 z_1 - K_r z_1^T \tanh(z_1) \|z_2\| - z_2^T K_p z_2 \\
&\quad + z_2^T (\hat{\vartheta}^T \Phi(\tilde{v}) - \vartheta^T \Phi(v)) - z_2^T e(t) - z_2^T \zeta_v
\end{aligned} \tag{39}$$

Conducting the norm operation and substituting the property of  $\tan$  type function in Lemma 3 into (39) to obtain:

$$\begin{aligned}\dot{V}_1 &\leq -z_1^T K_1 z_1 - \|K_r\| \|z_1\| \|z_2\| + 0.2785 \|K_r\| \|z_2\| \\ &\quad - z_2^T K_p z_2 + z_2^T \left( \hat{\vartheta}^T \Phi(\tilde{v}) - \hat{\vartheta}^T \Phi(v) - \tilde{\vartheta}^T \Phi(v) \right) \\ &\quad - z_2^T e(t) - z_2^T \zeta_v \\ &\leq -z_1^T K_1 z_1 + 0.2785 \|K_r\| \|z_2\| - z_2^T K_p z_2 \\ &\quad + \|z_2\| \|\hat{\vartheta}^T \Phi(\tilde{v}) - \hat{\vartheta}^T \Phi(v)\| + \|z_2\| \|\tilde{\vartheta}^T \Phi(v)\| \\ &\quad + \|z_2\| \|e(t)\| + \|z_2\| \|\zeta_v\|\end{aligned}\quad (40)$$

Introducing the inequation of triggered errors in the event condition with the Assumption 3, (40) transforms to:

$$\begin{aligned}\dot{V}_1 &\leq -z_1^T K_1 z_1 + 0.2785 \|K_r\| \|z_2\| - z_2^T K_p z_2 \\ &\quad + \|z_2\| \left( 1 + \|\hat{\vartheta}\| L_\Phi \right) \|e(t)\| + \|z_2\| \|\tilde{\vartheta}\| \|\Phi(v)\| + \|z_2\| \|\zeta_v\| \\ &\leq -z_1^T K_1 z_1 + 0.2785 \|K_r\| \|z_2\| - z_2^T K_p z_2 \\ &\quad + k_s \|z_2\| \|\Gamma(t)\| + \|z_2\| \|\hat{\vartheta}\| \|\Phi(v)\| + \|z_2\| \|\zeta_v\|\end{aligned}\quad (41)$$

as  $\|\Gamma(t)\| \leq \|z_1\| + K_p \|z_2\| + \|\hat{\vartheta}\| \|\Phi(\tilde{v})\|$  according to (28). Then, (41) can be converted into:

$$\begin{aligned}\dot{V}_1 &\leq -z_1^T K_1 z_1 + 0.2785 \|K_r\| \|z_2\| - z_2^T K_p z_2 \\ &\quad + k_s \|z_2\| \left( \|z_1\| + \|K_p\| \|z_2\| + \|\hat{\vartheta}\| \|\Phi(\tilde{v})\| \right) \\ &\quad + \|z_2\| \|\tilde{\vartheta}\| \|\Phi(v)\| + \|z_2\| \|\zeta_v\| + k_s \|z_2\| \zeta e^{-\beta t_k} \\ &\leq -z_1^T K_1 z_1 + 0.2785 \|K_r\| \|z_2\| - z_2^T K_p z_2 \\ &\quad + k_s \|z_2\| \|z_1\| + k_s \|K_p\| \|z_2\|^2 + k_s \|z_2\| \|\hat{\vartheta}\| \|\Phi(\tilde{v})\| \\ &\quad + \|z_2\| \|\tilde{\vartheta}\| \|\Phi(v)\| + \|z_2\| \|\zeta_v\| + k_s \|z_2\| \zeta e^{-\beta t_k} \\ &= -z_1^T K_1 z_1 - z_2^T K_p z_2 + 0.2785 \|K_r\| \|z_2\| + k_s \|K_p\| \|z_2\|^2 \\ &\quad + k_s \|z_2\| \|\hat{\vartheta}\| \|\Phi(\tilde{v})\| + \|z_2\| \|\tilde{\vartheta}\| \|\Phi(v)\| + \|z_2\| \|\zeta_v\| \\ &\quad + k_s \|z_2\| \zeta e^{-\beta t_k}\end{aligned}\quad (42)$$

Based on Young's inequality, the following results are obtained:

$$0.2785 \|K_r\| \|z_2\| \leq \frac{(0.2785 \|K_r\|)^2}{2} + \frac{1}{2} \|z_2\|^2 \quad (43)$$

$$k_s \|z_2\| \|\hat{\vartheta}\| \|\Phi(\tilde{v})\| \leq \frac{k_s^2}{2} \|z_2\|^2 + \frac{1}{2} \|\hat{\vartheta}\|^2 \|\Phi(\tilde{v})\|^2 \quad (44)$$

$$\|z_2\| \|\tilde{\vartheta}\| \|\Phi(v)\| \leq \frac{1}{2} \|z_2\|^2 + \frac{1}{2} \|\tilde{\vartheta}\|^2 \|\Phi(v)\|^2 \quad (45)$$

$$\|z_2\| \|\zeta_v\| \leq \frac{1}{2} \|z_2\|^2 + \frac{1}{2} \|\zeta_v\|^2 \quad (46)$$

$$k_s \|z_2\| \zeta e^{-t_k} \leq \frac{k_s}{2} \|z_2\|^2 + \frac{k_s}{2} \zeta^2 e^{-2\beta t_k} \quad (47)$$

Substituting the above results (43)–(46) into (42) leads to:

$$\begin{aligned}\dot{V}_1 &\leq -z_1^T K_1 z_1 - z_2^T K_p z_2 + \frac{(0.2785 \|K_r\|)^2}{2} + \frac{3}{2} \|z_2\|^2 \\ &\quad + k_s \|K_p\| \|z_2\|^2 + \frac{1}{2} \|\hat{\vartheta}\|^2 \|\Phi(\tilde{v})\|^2 + \frac{1}{2} \|\tilde{\vartheta}\|^2 \|\Phi(v)\|^2 \\ &\quad + \frac{k_s^2}{2} \|z_2\|^2 + \frac{k_s}{2} \|z_2\|^2 + \frac{k_s}{2} \zeta^2 e^{-2\beta t_k} + \frac{1}{2} \|\zeta_v\|^2 \\ &\leq -z_1^T K_1 z_1 - z_2^T \left( K_p - \left( \frac{k_s}{2} + \frac{k_s^2}{2} + k_s \|K_p\| + \frac{3}{2} \right) I \right) z_2 \\ &\quad + \frac{(0.2785 \|K_r\|)^2}{2} + \frac{1}{2} \|\hat{\vartheta}\|^2 \|\Phi(\tilde{v})\|^2 + \frac{1}{2} \|\tilde{\vartheta}\|^2 \|\Phi(v)\|^2 \\ &\quad + \frac{k_s}{2} \zeta^2 e^{-2\beta t_k} + \frac{1}{2} \|\zeta_v\|^2 \\ &\leq -\psi V_1 + M\end{aligned}\quad (48)$$

where  $\psi = \min(\psi_1, \psi_2)$  with  $\psi_1, \psi_2$  being defined as:

$$\psi_1 = \lambda_{\min}(2K_1) \quad (49)$$

$$\psi_2 = \frac{\lambda_{\min} \left( 2K_p - \left( k_s + k_s^2 + k_s \|K_p\| + \frac{3}{2} \right) I \right)}{(\lambda_{\max}(M_m(q_m)))} \quad (50)$$

and  $M$  is expressed as follows:

$$\begin{aligned}M &= \frac{(0.2785 \|K_r\|)^2}{2} + \frac{1}{2} \|\hat{\vartheta}\|^2 \|\Phi(v)\|^2 + \frac{1}{2} \|\tilde{\vartheta}\|^2 \|\Phi(v)\|^2 \\ &\quad + \frac{1}{2} \|\zeta_v\|^2 + \frac{k_s}{2} \zeta^2 e^{-2\beta t_k}.\end{aligned}\quad (51)$$

For the addressed system, the initial parameter is bounded, that is,  $0 \leq V_1(0) \leq k_v, k_v > 0$ . According to Lemma 1, we know that  $\dot{V}_1 < 0$ , indicating the uniformly boundedness if  $V_1 > \frac{M}{\psi}$  with  $\psi > 0$  and  $M > 0$ . Apparently,  $M$  is a positive value from (51), and  $\psi$  is positive when  $K_1 > 0, 2K_p - k_s - 2\left(\frac{k_s^2}{2} - k_s \|K_p\| - \frac{3}{2}\right)I > 0$ .

Another case considers the stability of the jumping at the triggered times. Constructing the difference of Lyapunov function as follows:

$$\begin{aligned}\Delta V_1 &= \frac{1}{2} z_1^{+T} z_1^+ - \frac{1}{2} z_1^T z_1 + \frac{1}{2} z_2^{+T} M_m(q_m) z_2^+ \\ &\quad - \frac{1}{2} z_2^T M_m(q_m) z_2 + \frac{1}{2} \sum_{i=1}^n \tilde{\vartheta}_i^{+T} \tilde{\vartheta}_i^+ - \frac{1}{2} \sum_{i=1}^n \tilde{\vartheta}_i^T \tilde{\vartheta}_i\end{aligned}\quad (52)$$

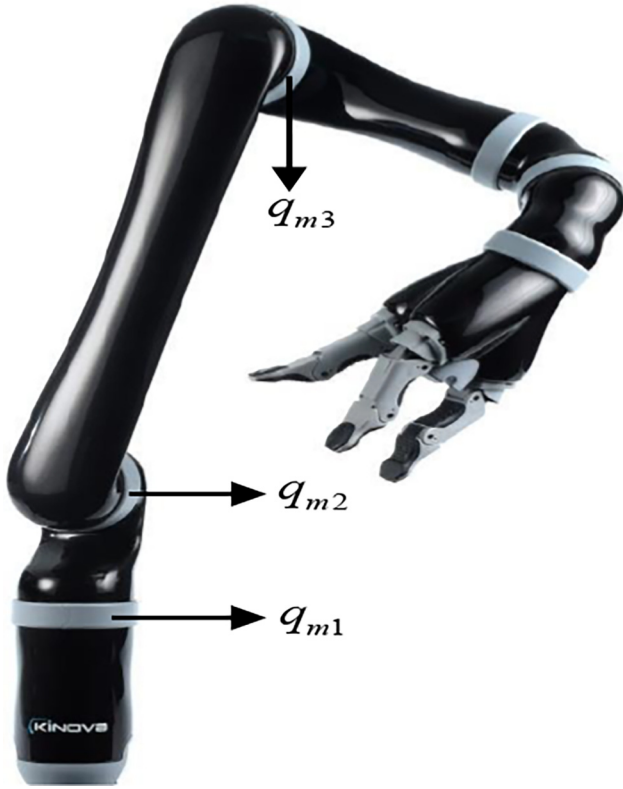
As  $z_1$  and  $z_2$  are time-continuous variable, one has:

$$\frac{1}{2} z_1^{+T} z_1^+ - \frac{1}{2} z_1^T z_1 + \frac{1}{2} z_2^{+T} M_m(q_m) z_2^+ - \frac{1}{2} z_2^T M_m(q_m) z_2 = 0$$

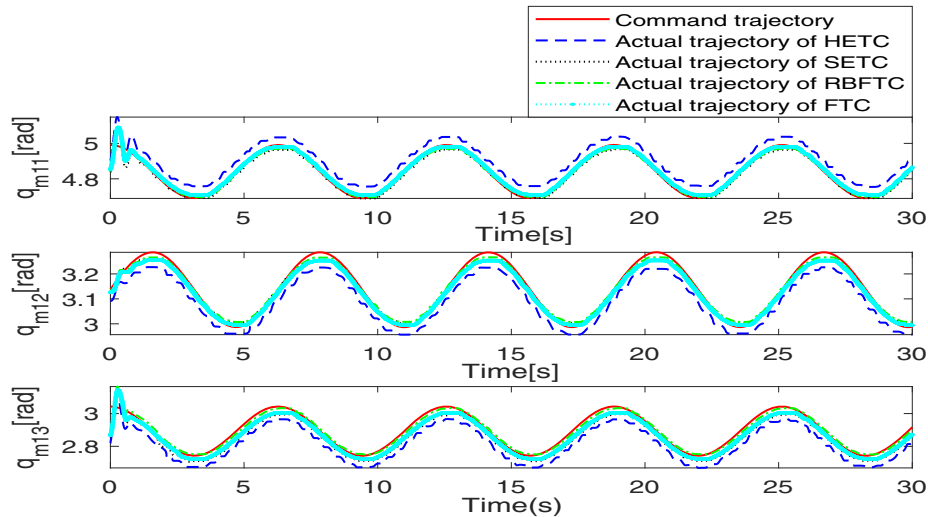
Then,  $\Delta V_1 < 0$  is true only when  $\sum_{i=1}^n \|\tilde{\vartheta}_i(t)\|^2 > \frac{2\chi_n}{\chi_1}$  according to (37). According to the above analyze, the uniformly ultimately boundness of all variables are proved.

Next, the feasibility of ETC with Zeno-free is illustrated by the following theorem.



**Figure 2** Structure of JACO2 robot**Table 1** DH parameters

$i$	$\alpha_i$	$a_i$	$d_i$	$q_{mi}$
1	$\pi/2$	0	-D1	$q_{m1}$
2	$\pi/2$	0	0	$q_{m2}$
3	$\pi/2$	0	-(D2+ D3)	$q_{m3}$
4	$\pi/2$	0	-e2	$q_{m4}$
5	$\pi/2$	0	-(D4+ D5)	$q_{m5}$
6	$\pi/2$	0	0	$q_{m6}$
7	$\pi$	0	-(D6+ D7)	$q_{m7}$

**Figure 3** Comparison results of tracking performance of three joints

**Theorem 3.** Consider the uncertain manipulator system under the effect of virtual signal in (14) and event-based controller in (19) and (23). Suppose all the properties and assumptions hold. When the controller and NN are updated along the “soft” law in (21) and aperiodic adaptive rule in (29) by the violation of event condition in (24) and (25), then the minimum time interval is lower bounded by a nonzero positive constant, which indicates that none of the Zeno behavior occurs.

**Proof.** Consider the following derivative inequation of the event triggered error  $e(t)$  for  $t_k \leq t < t_{k+1}$  (Liu et al., 2020; Tripathy et al., 2014):

$$\frac{d}{dt} \|e(t)\| = \frac{d}{dt} \sqrt{e(t)^T e(t)} \leq \|\dot{e}(t)\| = \|\dot{\Gamma}\| \quad (53)$$

Integrating both sides of (53) in the time interval  $[t_k^+, t]$  with  $t_0 = 0$  to get:

$$\int_{t_k^+}^t \frac{d}{ds} \|e(s)\| ds \leq \int_{t_k^+}^t \|\dot{\Gamma}\| ds, t_k \leq t < t_{k+1} \quad (54)$$

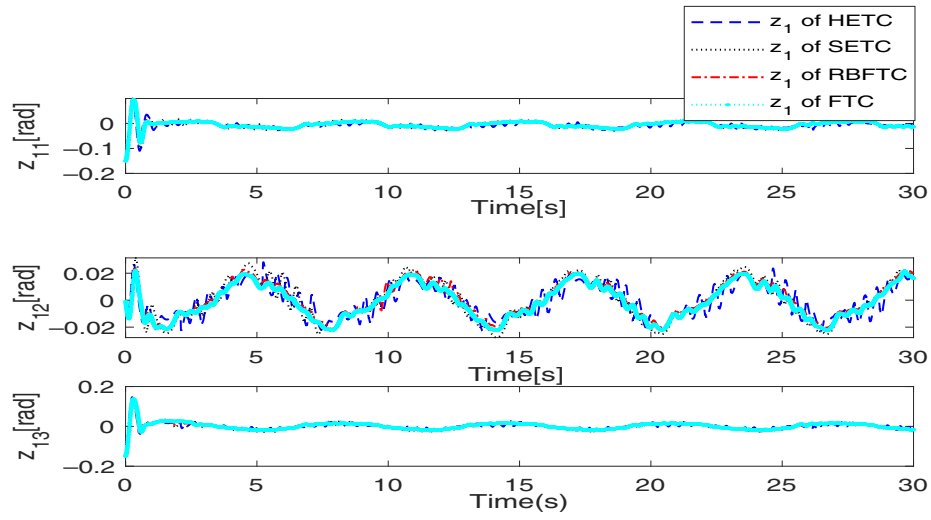
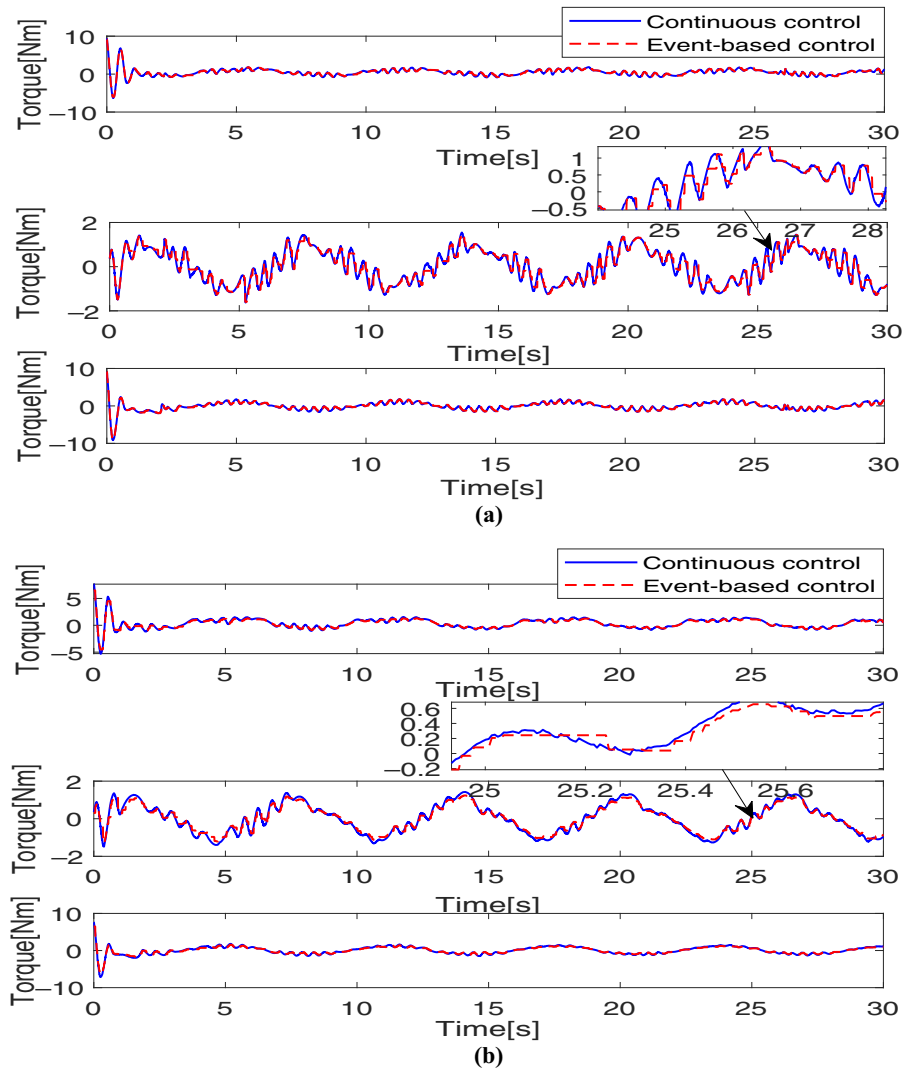
where  $t_k^+$  is the time just after  $t_k$ .

According to (15) and (23), one has:

$$\begin{aligned} \dot{\Gamma} = & K_1 z_1 - z_2 + k_s \tanh(z_1) \|z_2\| - K_p M_m^{-1}(q_m) [-z_1 \\ & - K_p z_2 + \hat{v}^T \Phi(\tilde{v}) - e(t) - V_m(q_m, \dot{q}_m) z_2 \\ & - V_m(q_m, \dot{q}_m) \alpha_1 - G_m(q_m) - M_m(q_m) \dot{\alpha}_1 - f_{dis}] \\ & t_k \leq t < t_{k+1} \end{aligned} \quad (55)$$

Taking the norm of both sides of (55), and substituting the NN identification as well as event condition, the following inequation is satisfied:

$$\begin{aligned} \|\dot{\Gamma}\| \leq & \|K_1\| \|z_1\| + \|z_2\| + |k_s| \|\tanh(z_1)\| \|z_2\| \\ & + \|K_p\| \|M_m^{-1}(q_m)\| [\|z_1\| + \|K_p\| \|z_2\| \\ & + \frac{k_s}{(1 + \|\hat{v}\| L_\Phi)} (\|z_1\| + \|K_p\| \|z_2\| + \|\hat{v}\| \|\Phi(\tilde{v})\|) \\ & + \|\hat{v}^T \Phi(\tilde{v})\| + \|\hat{v}^T \Phi(v)\| + \|V_m(q_m, \dot{q}_m)\| \|z_2\|] \end{aligned} \quad (56)$$

**Figure 4** Comparison results of tracking error of three joints**Figure 5** Control torque of three joints: (a) the traditional HETC and (b) the proposed SETC

It has been proved that all the signals on the right-hand side of (56) are bounded. As such, there exists a positive constant  $\Gamma_M$  such that the following inequation is satisfied, namely,  $\|\dot{\Gamma}\| \leq \Gamma_M$ . Substituting the bound value  $\Gamma_M$  into (54) results in:

$$\|e(t)\| - \|e(t_k^+)\| \leq \int_{t_k^+}^t \Gamma_M ds = \Gamma_M(t - t_k^+), t_k \leq t < t_{k+1} \quad (57)$$

Noting that  $e(t_k^+) \neq 0$ , its value can be written as the following form:

$$\begin{aligned} e(t_k^+) &= \Gamma(t_k^+) - \check{\Gamma}(t_k^+) \\ &= \beta(\Gamma(t_k) - \check{\Gamma}(t_k)) - \beta\check{\Gamma}(t_k) + \beta^2\check{\Gamma}(t_k) \\ &= \beta e(t_k) - \beta(1 - \beta)\check{\Gamma}(t_k) \end{aligned} \quad (58)$$

By using the inequality of matrix norm, one has:  $\|e(t_k^+)\| \leq \beta\|e(t_k)\| + \beta(1 - \beta)\|\check{\Gamma}(t_k)\|$ . Then, (57) is rewritten as:

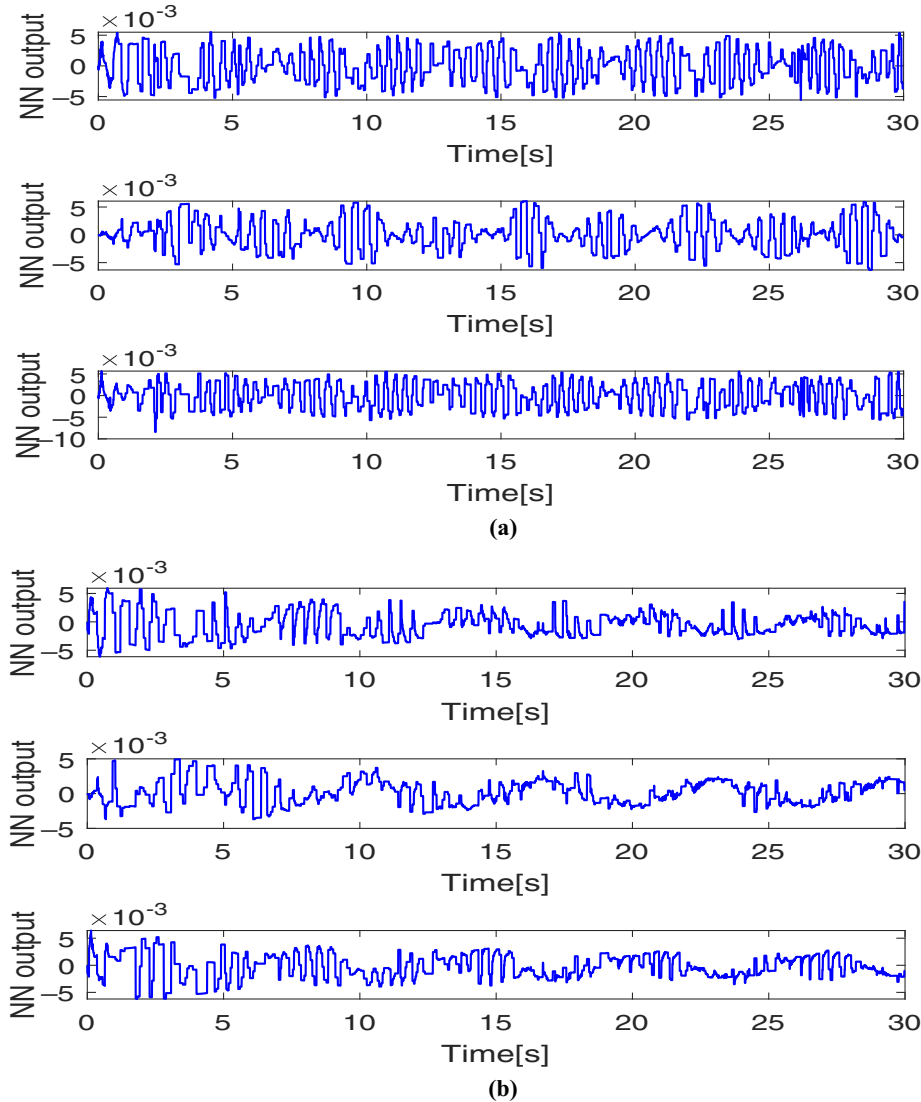
$$\begin{aligned} \|e(t)\| &\leq \Gamma_M(t - t_k^+) + \beta\|e(t_k)\| + \beta(1 - \beta)\|\check{\Gamma}(t_k)\| \\ t_k &\leq t < t_{k+1} \end{aligned} \quad (59)$$

The interval  $\Delta t_k = t_{k+1} - t_k^+$  at which events are emitted is the time it takes for the error  $\|e(t)\|$  to evolve to  $\gamma_2(\Gamma(t))$  according to the event condition. For  $t = t_{k+1}$ , one has  $\|e(t_{k+1})\| > \gamma_2(\Gamma(t_{k+1}))$ . Based on the above description, the time interval satisfies the following inequality:

$$\Delta t_k \geq \frac{\gamma_2(\Gamma(t_{k+1})) - \beta\|e(t_k)\| - \beta(1 - \beta)\|\check{\Gamma}(t_k)\|}{\Gamma_M} \quad (60)$$

Substituting the definition of  $\gamma_2(\Gamma(t))$  in the event condition (27), one has  $\Delta t_k \geq \frac{k_s}{(1 + \|\dot{\vartheta}\|L_\Phi)\Gamma_M} \zeta e^{-\beta t_k} > 0$ . As such, Zeno behavior is excluded.

**Figure 6** Approximation of the NN: (a) the traditional HETC and (b) the proposed SETC



Remark 3. The parameters of the proposed triggered controller include control gains  $K_1$ ,  $K_r$  and  $K_p$ ; the updating coefficient of NN  $v_1$  and  $\rho_1$ ; and the parameters of triggered mechanism  $k_s$  and  $\beta_1$ .

The parameters like  $K_1$ ,  $K_r$  and  $K_p$  are reflected both in the final bound of control error and the time interval [see (51) and (60)]; The parameter  $K_r$  is reflected in the final bound of control error [see (51)]; The parameter  $\beta_1$  is reflected in the time interval of adjacent events [see (60)]; The parameters like  $v_1$  and  $\rho_1$  are reflected in the final upper bound of network's weights [see (37)].

The selection of  $K_1$ ,  $K_r$ ,  $K_p$ ,  $v_1$  is mainly based on the parametric conditions of Lyapunov stability [see (49), (50) and (51)]. Other parameters like  $\rho_1$  and  $\beta_1$  can be set by the designer according to the task performance requirements.

## 5. Simulation

In this paper, to demonstrate the effectiveness and superiority of the proposed method in realizing the stable tracking control, the hardware experiment based on the Kinova JACO2

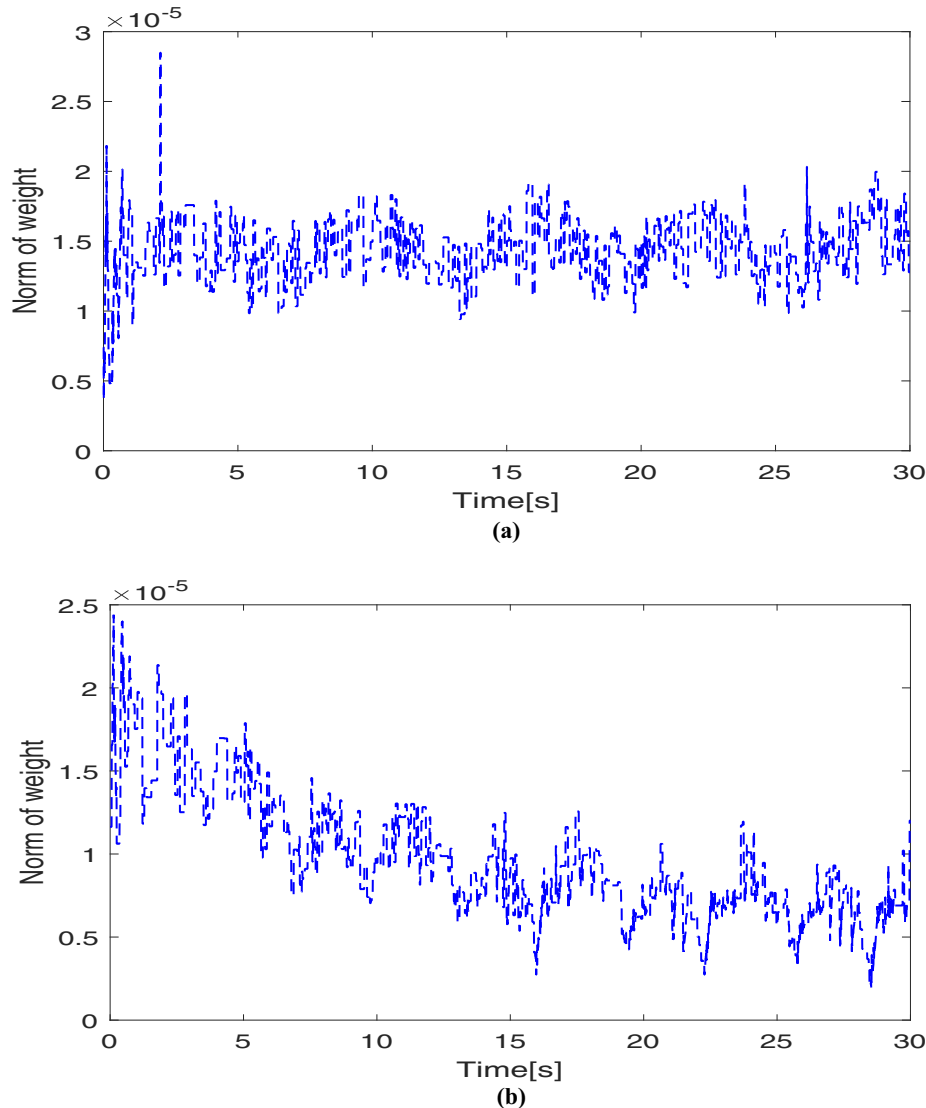
manipulator (see Figure 2) is conducted. The computer that runs the robot control program is configured as Intel(R) Core (TM) i5-7200CPU@2.50 GHz 2.70GHz RAM 8.00GB, and the control program is made in MATLAB 2018b. Data interaction between manipulator and computer is realized through the universal serial bus connection. The Denavit-Hartenberg parameters of the manipulator are listed in Table 1, in which the specific parameter are set as:

$D1 = 0.2755m$ ,  $D2 = 0.2050m$ ,  $D3 = 0.2050m$ ,  $D4 = 0.2073m$ ,  $D5 = 0.1038m$ ,  $D6 = 0.1038m$ ,  $D7 = 0.1600m$  and  $e2 = 0.0098m$ .

In the experiment, only joints  $q_{m1}$ ,  $q_{m2}$  and  $q_{m3}$  are controlled to ensure that Cartesian space has no position redundancy. The desired trajectory (the units are in rad)  $q_{md}$  for tracking is designed as:

$$x_c(t) = \begin{bmatrix} q_{md1} \\ q_{md2} \\ q_{md3} \end{bmatrix} = \begin{bmatrix} \rho_1 + \rho_1 \cos(\pi t) \\ \rho_2 + \rho_2 \sin(\pi t) \\ \rho_3 + \rho_3 \cos(2\pi t) \end{bmatrix} \quad (61)$$

Figure 7 Varies of weight of three joints: (a) the traditional HETC and (b) the proposed SETC



where the values of amplitude are set as:  $\rho_1 = \rho_2 = \rho_3 = 0.15$ .

The initial location of the joint is chosen as  $q_{m1}(0) = 0.2 \text{ rad}$ ,  $q_{m2}(0) = 0.15 \text{ rad}$  and  $q_{m3}(0) = 0.1 \text{ rad}$ . The initial velocity is set as  $\dot{q}_{m1}(0) = 0 \text{ rad/s}$ ,  $\dot{q}_{m2}(0) = 0 \text{ rad/s}$  and  $\dot{q}_{m3}(0) = 0 \text{ rad/s}$ . The total length of simulation is 30 s with the maximum number of sampling points being 4,000. The disturbance is introduced as follows:

$$f_{dis}(t) = \begin{bmatrix} f_{dis1} \\ f_{dis2} \\ f_{dis3} \end{bmatrix} = \begin{bmatrix} 0.1 \sin(\pi t) \cos(2\pi t) \\ 0.15 \cos(\pi t) \\ 0.01 \end{bmatrix} \quad (62)$$

The configuration of the whole control is designed here. Gain parameters are set as:

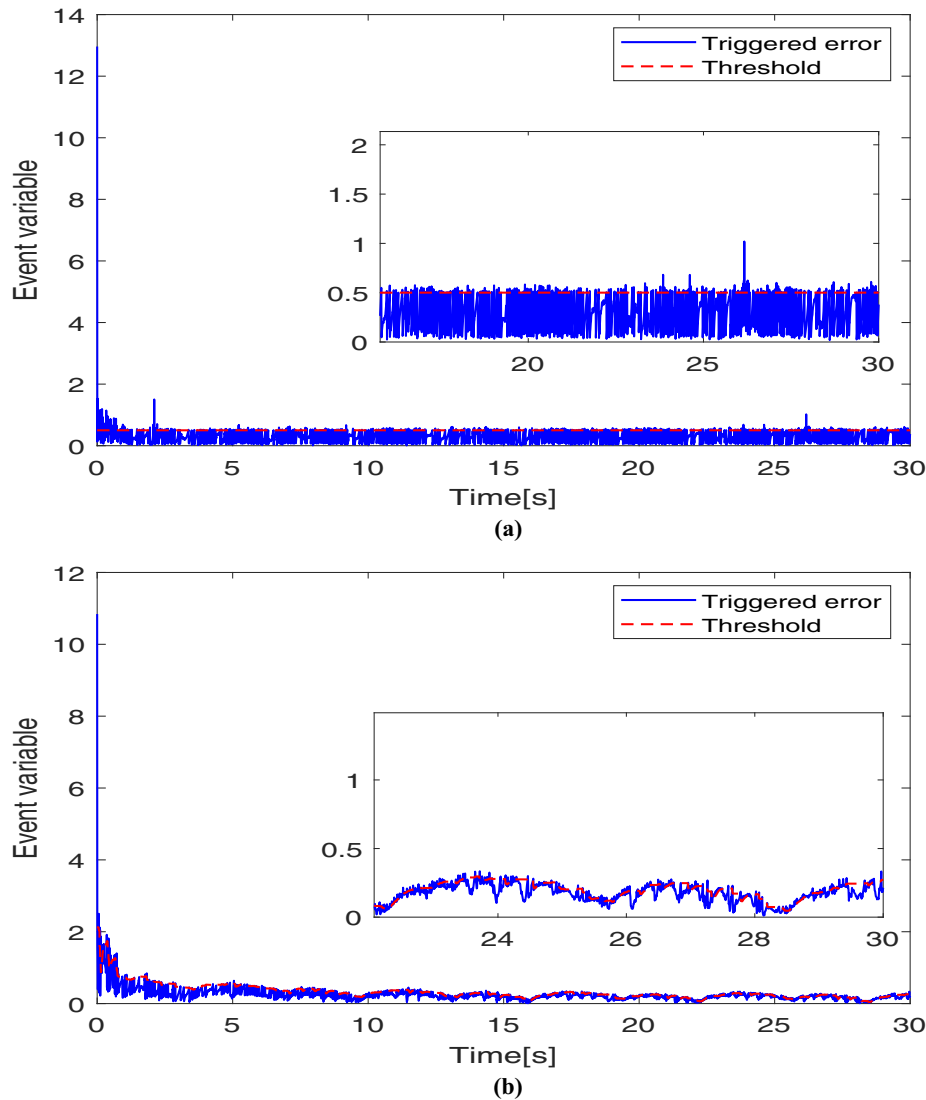
$K_1 = \text{diag}([30, 25, 25])$ ,  $K_p = \text{diag}([1, 0.9, 0.9])$ ,  $K_s = \text{diag}([0.01, 0.01, 0.01])$ . The initial weight is designed as  $\hat{v}_i(0) = [0, 0, \dots, 0]^T \in \mathbb{R}^{2^{12} \times 1}$ . The updating coefficient is designed as:  $c = 1$ ,  $L_s = \begin{bmatrix} 1, 1, 1 \\ 1, 1, 1 \end{bmatrix}^T$  and  $v = 1$ . The size of NN

input  $\tilde{v}$  is 12. The number of hidden nodes is set as  $l = 2^{12}$ . The center of activation function  $\Phi(\tilde{v})$  is chosen as  $[-1, 1] \times [-1, 1] \times [-1, 1] \times \dots \times [-1, 1]$ . In general, the

$n=12$

center value can be determined via the empirical approach or the training method, and the center value of 1 or  $-1$  could represent the primary components of most data and brings the satisfactory accuracy in discrimination and estimation. Other parameters for the event condition are set as:  $L_\phi = 0.05$  and  $\beta = 0.2$ . To illustrate the effectiveness of our method in depressing the chattering-induced instability and communication burden with guaranteed tracking performance, our method is compared with the traditional ZOH-based hard ETC method in Zhao *et al.* (2021), Qiu *et al.* (2021), Gao *et al.* (2021a) and two time continuous adaptive control methods in Li *et al.* (2021a, 2021b). For the sake of distinction, the proposed “soft” ETC method and the traditional “hard” ETC method is called SETC and HETC for short, the RBFNN-

**Figure 8** Threshold and event error: (a) the traditional HETC and (b) the proposed SETC



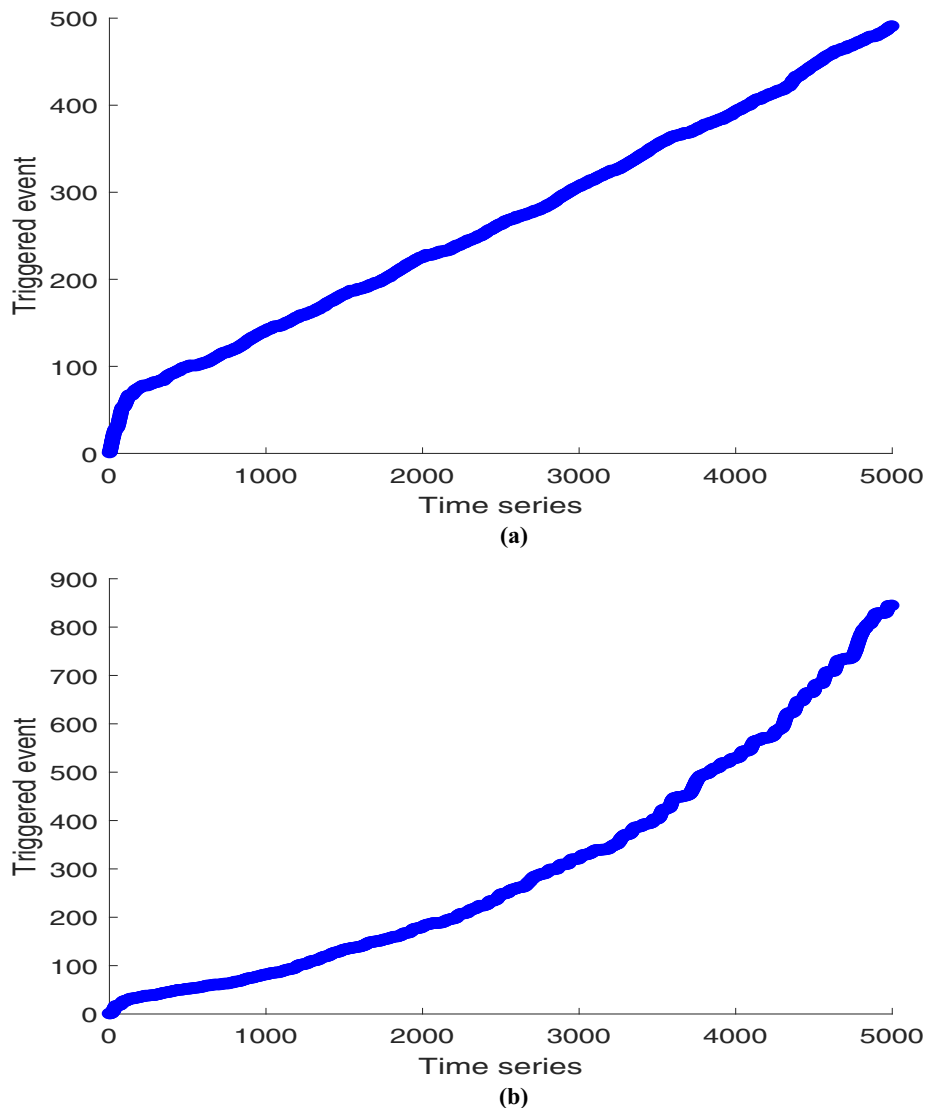


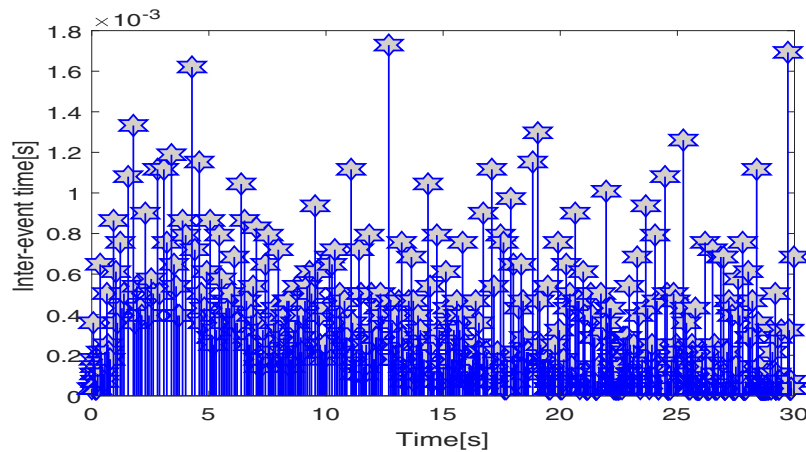
based time continuous method in Li *et al.* (2021a) and the fuzzy NN-based time continuous method in Li *et al.* (2021b) is called RBFTC and FTC for short.

The experimental results are portrayed in Figures 3–8. Figure 3 exhibits the fitting of actual joint position to expected trajectories. It can be seen that the actual trajectory corresponding to the continuous adaptive network control method named RBFTC and FTC follow the desired one, accurately. In addition, the proposed SETC method has slower oscillation than the traditional HETC method. Figure 4 shows the position tracking error of three joints, where the variation of error curve of the proposed SETC is kept small and basically consistent with that of continuous RBFTC and FTC method, whereas the error of HETC has large vibration. The control signal is depicted in Figure 5; it is clear from the partial enlargement of Figure 5(a) and 5(b) that the red-dotted line corresponding to the event-sampled torque has a discontinuous property. In addition, one can see from Figure 5(b) that through developing the “soft” method, the jumping change has been alleviated. Figure 6 shows

the approximation result of the NN, and affected by the discontinuous updating, the network’s output has chattering property. Figure 7 describes the change of the weight, where the weight in Figure 7(b) has an obvious convergence based on the proposed MPL adaptive law. Figure 8 provides the variation of the event-triggered error and threshold of two event-triggered methods, where the error varies within the threshold. It is worth noting from Figure 8(a) that a noticeable chattering occurs in the error curve around the switch surface of threshold, whereas this chattering effect is largely reduced by our proposed “soft” mechanism in Figure 8(b). Figure 9 shows that around 500 and 800 events are obtained by the traditional and proposed triggering method, respectively. While the total sampling number of time is 5,000, which indicates that the event-triggered mechanism can effectively reduce the burden of communication and computation without causing significant degradation of system performance. Moreover, through the comparison of Figure 9(a) and 9(b), it can be known that our proposed method produces more events than the traditional ETC through

**Figure 9** Number of events: (a) the traditional HETC and (b) the proposed SETC



**Figure 10** Time interval of two adjacent events

designing a “soft” method, and this mechanism will lead to a decline of control differences at triggered instants, such that the chattering effect can be reduced to guarantee the control performance. Figure 10 shows that the time interval of two adjacent events keeps positive.

## 6. Conclusion

In this article, the tracking control with uncertain system dynamics and constrained communication in the control-execution channel is considered. To deal with the above problems, an adaptive event-triggered controller with aperiodic estimation is constructed to realize the discontinued transmission of control signals. In the construction of event-triggered mechanism, the chattering effect is first to be addressed by proposing a novel “soft” mechanism to adjust the control updating, which increases the flexibility of communication modulation. In addition, the adaptive law with minimum learning parameters principle is designed for a trade-off between accuracy and triggering frequency. Aiming at the above design, a novel dead-zone condition with variable boundary is designed to avoid Zeno-behavior. Finally, the validity of our method is proved by both theory and hardware experiments. The experiment results show the superiority of the proposed method in reducing control chattering and improving accuracy compared with the traditional triggered control method, although at the expense of increased communication burden. In future works, triggered control methods can be further designed to minimize communication burden as much as possible with guaranteed triggered control stability.

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