Adaptive Event-triggered Control with Prescribed Performance for Nonlinear System with Full-state Constraints

Decai Liu, Xinyu Ouyang*, Nannan Zhao, Yu Luo

***Abstract*—An adaptive event-triggered tracking control method with preset performance is proposed for a class of uncertain nonlinear systems with full-state constraints and unknown time-varying disturbances. Firstly, a performance function is designed and the original system error is converted. In order to eliminate the influence of state constraints on the system, a barrier Lyapunov function is introduced. Secondly, the influence of unknown function is solved by using radial basis function neural network (RBFNN). Simultaneously, event-triggering mechanism was used to reduce the update frequency of control signals, thereby the communication burden is reduced. Then, based on the Lyapunov stability theorem, all signals of the closed-loop control system are verified to be bounded, all states do not violate the predefined interval, and the Zeno behavior does not occur. Finally, the effectiveness of the proposed method was verified using a single-link flexible manipulator as a simulation example.**

***Index Terms*—nonlinear system, event-triggered control, prescribed performance, full-state constraints, flexible manipulator.**

I. Introduction

THE control problem of nonlinear system has always been a hot issue in the control field [1]–[4]. Especially in recent decades, the systems have become more and more complex, and people's requirements for the control system have become higher and higher. The unknown nonlinear problems and uncertain factors bring difficulty to the control of the system. For solving these problems, adaptive control for uncertain nonlinear systems has been widely studied and practiced on the basis of neural networks and fuzzy logic systems [5]–[7]. However, the various constraints of the system also bring new problems to the control of the system. Considering the security of the system and the higher requirements for implementation, constraints such as state constraints and input/output constraints generally exist in practical systems such as flexible manipulators [8]–[10]. To address these issues, scholars have conducted extensive research [11]–[13]. In [14], an adaptive tracking control strategy based on instruction filtering was given by using the barrier Lyapunov function, which not only ensured the stability of the system, but also made all the states of the system not violate the preset interval. Different from logarithmic barrier Lyapunov function, by introducing a tan barrier Lyapunov function and combining with RBFNN, Lu et al. [15] designed an adaptive event-triggered controller for a class of stochastic nonlinear systems with full state constraints. However, the above researches only focused on the impact of state constraints, without considering how to improve the transient and steady-state performance of the system, which is equally important in practical production.

Prescribed performance control (PPC) method not only ensures system stability, but also takes into account both transient and steady-state performance of the system [16]. In [17], the boundedness and steady-state error of the system were effectively controlled due to the introduction of dynamic surface control with prescribed performance, but the author only considered the case of input saturation, which may make the system performance unsatisfactory when other constraints appear. On this basis, [18] designed an accelerated adaptive fuzzy neural prescribed performance controller for permanent magnet synchronous motor (PMSM), and solved the problems of full-state constraint, uncertain time delay and so on. Mu et al. [19] proposed an adaptive neural network output feedback control method for a class of double switched nonlinear systems with time-delay, which ensures that the tracking performance meets the predetermined performance well.

In recent years, with the development of network control systems, the issue of communication resource allocation has received significant attention [20]. Event-triggered control (ETC) can effectively reduce the communication burden by only updating control signals when necessary [21], [22]. In [23], by introducing the event-triggered mechanism, the amount of online training calculation was reduced and data transmission resources were saved. Moreover, the stability of the system can be well satisfied. In [24], aiming at a class of single input single output non-affine nonlinear systems, the authors proposed an event-triggered based adaptive tracking control method through output feedback, which ensures approximate minimization of system performance indicators while reducing computational and transmission loads.

On the basis of the foregoing discussion, this paper proposes an adaptive control strategy of neural network with prescribed performance based on event-triggered for a class of uncertain strict-feedback nonlinear systems with full-state constraints and unknown time-varying disturbances. Based on [25] and [26], the control scheme proposed in this paper can not only ensure that the system meets the

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constraints, but also make the system error converge better. During the controller design process, a new parameter is introduced to replace the ideal weight vector of neural network, which saves the number of adjustment parameters. In addition, unlike the fixed threshold event-triggered adopted in [27], this paper introduces a relative threshold event-triggered mechanism, which reduces the number of event triggering while ensuring the expected performance. Finally, the proposed method was validated by using actual numerical examples.

II. SYSTEM DESCRIPTIONS AND BASIC KNOWLEDGE

A. problem formulation

A class of nonlinear systems with full-state constraints and unknown time-varying disturbances is considered as follows:

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i) + x_{i+1} + d_i(t), 1 \le i \le n-1 \\ \dot{x}_n = f_n(\bar{x}_n) + u + d_n(t) \\ y = x_1. \end{cases} \tag{1}$$

Where $\bar{x}_i = [x_1, x_2, \cdots, x_i]^{\mathrm{T}} \in R^i$ and $y \in R$ are the states and output of the system, respectively; $f_i (i = 1, 2, \cdots, n)$ are the unknown smooth functions. In addition, $d_i(t) (i = 1, 2, \cdots, n)$ are the unknown external disturbances.

Control objective: Design an event-triggered adaptive control scheme for the system (1), which makes the system tracking error y_d converge to the preset error range within a preset time, and ensures that all signals in the closed-loop system are bounded and do not violate the state constraints.

For subsequent analysis, the following assumptions are given.

Assumption 1. The unknown disturbances $d_i(t) (i = 1, 2, \cdots, n)$ are bounded, and there exists positive constants $\bar{d_i}$ that makes $|d_i| \le \bar{d_i}, i = 1, 2, ..., n$.

Assumption 2. The reference signal y_d and the derivative ${y_d}^{(i)}$ are known and bounded.

Assumption 3. All states of the system hold $|x_i| < k_{ci}$, here k_{ci} is a normal number.

B. Basic knowledge

Definition 1. [28] For a smooth continuous function $\rho(t) : R_+ \to R_+$, if $\rho(t)$ is positive and strictly decreasing, $\lim_{t \to \infty} \rho(t) = \rho_\infty > 0$, it is called a performance function. In this paper, the following default performance function will be selected:

$$\rho(t) = (\rho_0 - \rho_\infty) e^{-lt} + \rho_\infty \tag{2}$$

Where ρ_0, ρ_∞, l are preset normal numbers.

Error transformation: $e(t) = \rho(t) S(\eta)$, where $e(t)=y(t)-y_d(t)$ is the tracking error of the original system, η is the new conversion error. Take $S(\eta) = \frac{e^\eta - e^{-\eta}}{e^\eta + e^{-\eta}}$, then $\eta(t) = \frac{1}{2} \ln \left[\frac{\rho(t)+e(t)}{\rho(t)-e(t)} \right]$.

Definition 2. [29] RBFNN can be stated as $f(Z) = {W^*}^T S(Z) + \tau(Z)$, where $S(Z) = [S_1(Z), ..., S_k(Z)]^T$ represents radial basis function vector, k represents the number of radial basis function nodes, $W = [W_1, W_2 ..., W_k]^{\mathrm{T}} \in R^k$ is the neural network weight vector. There are many choices of basis functions, and Gaussian function is usually selected as radial basis function.

The following lemmas are introduced for achieving the control objective of the system.

Lemma 1. [30] $f(Z)$ is a continuous function defined in a compact set $\Omega \in R^n$, and there is a constant weight vector W^*, which makes the following formula hold:

$$f(Z) = {W^*}^T S(Z) + \tau(Z) \tag{3}$$

$$W^* = \arg \min_{W \in R^k} \left\{ \sup_{Z \in \Omega} \left| f(Z) - W^T S(Z) \right| \right\} \tag{4}$$

Where $W^* = [{W_1}^*, ...{W_2}^*, {W_k}^*]^T \in R^k$ is the optimal weight, $\tau(Z)$ is the approximation error, and it satisfies $\tau(Z) \le \bar{\tau}$, $\bar{\tau} > 0$.

Lemma 2. [31] There is a normal number $\iota > 0$, and the function $\tanh(\cdot)$ satisfies

$$0 \le |x| - x \tanh(\frac{x}{\iota}) \le 0.2785\iota \tag{5}$$

Lemma 3. [32] For a system with bounded initial conditions, if there is a continuously differentiable and positive definite function $V(x,t)$, it satisfies $k_1(|x|) \le V(x,t) \le k_2(|x|)$, $\dot{V} \le -CV + D$, where C, D are normal numbers and $0 \le V(t) \le V(0)e^{-Ct} + D/C$, then the solution of the system is semi-globally uniformly and finally bounded.

Lemma 4. [33] For a and b, there has

$$xy \le \frac{p^a}{a} |x|^a + \frac{1}{bp^b} |y|^b \tag{6}$$

Where $p > 0$, $a > 1$, $b > 1$, and $(a-1)(b-1) = 1$.

III. Adaptive controller design

A. Controller design

In order to design the controller conveniently, a set of state coordinate transformations are introduced first.

$$\begin{cases} z_1 = x_1 - y_d \\ z_i = x_i - \alpha_{i-1}, i = 2, ..., n. \end{cases} \tag{7}$$

Where $\alpha_i (i = 1, 2, \cdots n-1)$ are virtual controllers.

Step 1: Introduce a new error transformation

$$\eta_1(t) = \frac{1}{2} \ln \left[\frac{\rho(t) + z_1(t)}{\rho(t) - z_1(t)} \right] \tag{8}$$

For convenience, $\eta_1(t)$, $\rho(t)$ and $z_1(t)$ are abbreviated as η_1, ρ and z_1. Derivation of η_1 can be obtained as follows

$$\dot{\eta}_1 = r \left[\dot{x}_1 - v \right] = r \left[f_1 + x_2 + d_1 - v \right] \tag{9}$$

Where $r = \frac{\rho}{\rho^2 - {z_1}^2}, v = \dot{y}_d + \frac{z_1 \dot{\rho}}{\rho}$.

Construct the following barrier Lyapunov function

$$V_1 = \frac{1}{2} \log \frac{{k_{b1}}^2}{{k_{b1}}^2 - {\eta_1}^2} + \frac{1}{2} \tilde{\theta}_1^2 \tag{10}$$

Where $k_{b1} = k_{c1} - A_1$ is a positive design parameter, $\tilde{\theta}_1 = \theta_1 - \hat{\theta}_1$, $\hat{\theta}_1$ is an estimated value of θ_1.

By using (1), (7) and (10), it can be obtained that

$$\dot{V}_1 = \frac{\eta_1 r}{{k_{b1}}^2 - {\eta_1}^2} (f_1 + z_2 + \alpha_1 + d_1 - v) - \tilde{\theta}_1 \dot{\hat{\theta}}_1 \tag{11}$$

According to Lemma 4, the following inequality holds

$$\frac{\eta_1 r}{{k_{b1}}^2 - {\eta_1}^2} d_1 \le \frac{{\eta_1}^2 r^2}{2({k_{b1}}^2 - {\eta_1}^2)^2} + \frac{\bar{d}_1^2}{2} \tag{12}$$

Substituting (12) for (11), there has

$$\begin{aligned}\dot{V}_1 \leq& \frac{\eta_1 r}{{k_{b1}}^2-{\eta_1}^2}\left[F_1(Z_1)+z_2+\alpha_1-v\right]\\&+\frac{\bar{d}_1^2}{2}-\tilde{\theta}_1\dot{\hat{\theta}}_1\end{aligned} \tag{13}$$

Where $F_1(Z_1)=f_1+\frac{\eta_1 r}{2({k_{b1}}^2-{\eta_1}^2)}, Z_1=[x_1,y_d,\dot{y}_d,\rho]$. Since f_1 is an unknown function, it cannot be directly used to construct a virtual control law, so it can be resolved by RBFNN

$$F_1(Z_1)={W_1}^{*T}S_1(Z_1)+\tau_1(Z_1) \tag{14}$$

Where ${W_1}^*$ is the optimal weight, $\tau_1(Z_1)\leq\bar{\tau}_1,\bar{\tau}_1>0$ and $\tau_1(Z_1)$ is the minimum approximation error. According to Lemma 4, there has

$$\begin{aligned}\frac{\eta_1 r}{{k_{b1}}^2-{\eta_1}^2}F_1(Z_1)\leq& \frac{{\eta_1}^2r^2\theta_1{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)^2}+\frac{{a_1}^2}{2}\\&+\frac{{\eta_1}^2r^2}{2({k_{b1}}^2-{\eta_1}^2)^2}+\frac{\bar{\tau}_1^2}{2}\end{aligned} \tag{15}$$

Where $\theta_1=\|{W_1}^*\|^2$, $a_1>0$, a_1 is the design parameter.

Substituting (15) into (13) yields

$$\begin{aligned}\dot{V}_1 \leq& \frac{\eta_1 r}{{k_{b1}}^2-{\eta_1}^2}\left[z_2+\alpha_1+\frac{\eta_1 r}{2({k_{b1}}^2-{\eta_1}^2)}\right.\\&\left.+\frac{\eta_1 r\theta_1{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)}-v\right]\\&+\frac{{a_1}^2}{2}+\frac{\bar{d}_1^2}{2}+\frac{\bar{\tau}_1^2}{2}-\tilde{\theta}_1\dot{\hat{\theta}}_1\end{aligned} \tag{16}$$

By using $\tilde{\theta}_1=\theta_1-\dot{\hat{\theta}}_1$, there has

$$\begin{aligned}\dot{V}_1 \leq& \frac{\eta_1 r}{{k_{b1}}^2-{\eta_1}^2}\left[z_2+\alpha_1+\frac{\eta_1 r}{2({k_{b1}}^2-{\eta_1}^2)}\right.\\&\left.+\frac{\eta_1 r\hat{\theta}_1{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)}-v\right]+\frac{{a_1}^2}{2}+\frac{\bar{d}_1^2}{2}+\frac{\bar{\tau}_1^2}{2}\\&+\tilde{\theta}_1\left[\frac{{\eta_1}^2r^2{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)^2}-\dot{\hat{\theta}}_1\right]\end{aligned} \tag{17}$$

Design a virtual controller and adaptive law as follows

$$\begin{aligned}\alpha_1=&-\lambda_1\frac{\eta_1}{r}-\frac{\eta_1 r}{2({k_{b1}}^2-{\eta_1}^2)}\\&-\frac{\eta_1 r\hat{\theta}_1{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)}+v\end{aligned} \tag{18}$$

$$\dot{\hat{\theta}}_1=-\sigma_1\hat{\theta}_1+\frac{{\eta_1}^2r^2{S_1}^TS_1}{2{a_1}^2({k_{b1}}^2-{\eta_1}^2)^2} \tag{19}$$

Where $\lambda_1>0$, $\sigma_1>0$ are design parameters, then $\dot{V}_1$ can be rewritten as

$$\dot{V}_1\leq-\lambda_1\frac{{\eta_1}^2}{{k_{b1}}^2-{\eta_1}^2}-\frac{1}{2}\sigma_1\tilde{\theta}_1^2+\frac{\eta_1 z_2 r}{{k_{b1}}^2-{\eta_1}^2}+C_1 \tag{20}$$

Where $C_1=\frac{{a_1}^2}{2}+\frac{\bar{d}_1^2}{2}+\frac{\bar{\tau}_1^2}{2}+\frac{1}{2}\sigma_1{\theta_1}^2$.

Step 2: Construct the following barrier Lyapunov function

$$V_2=V_1+\frac{1}{2}\log\frac{{k_{b2}}^2}{{k_{b2}}^2-{z_2}^2}+\frac{1}{2}\tilde{\theta}_2^2 \tag{21}$$

Where $\tilde{\theta}_2=\theta_2-\hat{\theta}_2$ is parameter estimation error, $\hat{\theta}_2$ is the estimated value of θ_2.

According to (7), we can get

$$\dot{z}_2=f_2+z_3+\alpha_2+d_2-\dot{\alpha}_1 \tag{22}$$

Then, derivation of V_2 is as follows

$$\begin{aligned}\dot{V}_2=&\dot{V}_1+\frac{z_2}{{k_{b2}}^2-{z_2}^2}\left[f_2+z_3+\alpha_2+d_2-\dot{\alpha}_1\right]\\&-\tilde{\theta}_2\dot{\hat{\theta}}_2\end{aligned} \tag{23}$$

According to Lemma 4 and Assumption 1, it has

$$\frac{z_2}{{k_{b2}}^2-{z_2}^2}d_2\leq\frac{{z_2}^2}{2({k_{b2}}^2-{z_2}^2)^2}+\frac{\bar{d}_2^2}{2} \tag{24}$$

Substituting (24) for (23), there has

$$\begin{aligned}\dot{V}_2\leq&\dot{V}_1+\frac{z_2}{{k_{b2}}^2-{z_2}^2}\left[F_2(Z_2)+z_3+\alpha_2\right]\\&+\frac{\bar{d}_2^2}{2}-\tilde{\theta}_2\dot{\hat{\theta}}_2-\frac{\eta_1 z_2 r}{{k_{b1}}^2-{\eta_1}^2}\end{aligned} \tag{25}$$

Where $F_2(Z_2)=f_2+\frac{z_2}{2({k_{b2}}^2-{z_2}^2)}-\dot{\alpha}_1+\frac{{k_{b2}}^2-{z_2}^2}{{k_{b1}}^2-{\eta_1}^2}\eta_1 r$, $Z_2=[x_1,x_2,y_d,\dot{y}_d,\ddot{y}_d,\theta_1,\rho]$.

Similarly, the RBFNN can be used to approach $F_2(Z_2)$:

$$F_2(Z_2)={W_2}^{*T}S_2(Z_2)+\tau_2(Z_2) \tag{26}$$

By using lemma 4, it has

$$\begin{aligned}\frac{z_2}{{k_{b2}}^2-{z_2}^2}F_2(Z_2)\leq&\frac{{z_2}^2\theta_2{S_2}^TS_2}{2{a_2}^2({k_{b2}}^2-{z_2}^2)^2}+\frac{{a_2}^2}{2}\\&+\frac{{z_2}^2}{2({k_{b2}}^2-{z_2}^2)^2}+\frac{\bar{\tau}_2^2}{2}\end{aligned} \tag{27}$$

Where $\theta_2=\|{W_2}^*\|^2$, $a_2>0$ is the design parameter. Then, substituting (27) into (25) yields

$$\begin{aligned}\dot{V}_2\leq&\dot{V}_1+\frac{z_2}{{k_{b2}}^2-{z_2}^2}\left[\frac{z_2\hat{\theta}_2{S_2}^TS_2}{2{a_2}^2({k_{b2}}^2-{z_2}^2)}\right.\\&\left.+\frac{z_2}{2({k_{b2}}^2-{z_2}^2)}+z_3+\alpha_2\right]+\frac{{a_2}^2}{2}+\frac{\bar{\tau}_2^2}{2}+\frac{\bar{d}_2^2}{2}\\&-\frac{\eta_1 r z_2}{{k_{b1}}^2-{\eta_1}^2}+\tilde{\theta}_2\left[\frac{{z_2}^2{S_2}^TS_2}{2{a_2}^2({k_{b2}}^2-{z_2}^2)^2}-\dot{\hat{\theta}}_2\right]\end{aligned} \tag{28}$$

Therefore, the virtual control signal is designed as follows

$$\alpha_2=-\lambda_2 z_2-\frac{z_2}{2({k_{b2}}^2-{z_2}^2)}-\frac{z_2\hat{\theta}_2{S_2}^TS_2}{2{a_2}^2({k_{b2}}^2-{z_2}^2)} \tag{29}$$

and adaptive law is designed as follows

$$\dot{\hat{\theta}}_2=-\sigma_2\hat{\theta}_2+\frac{{z_2}^2{S_2}^TS_2}{2{a_2}^2({k_{b2}}^2-{z_2}^2)^2} \tag{30}$$

Where $\lambda_2>0$, $\sigma_2>0$ are design parameters, then $\dot{V}_2$ can be rewritten as

$$\begin{aligned}\dot{V}_2\leq&-\lambda_1\frac{{\eta_1}^2}{{k_{b1}}^2-{\eta_1}^2}-\lambda_2\frac{{z_2}^2}{{k_{b2}}^2-{z_2}^2}\\&-\frac{1}{2}\sigma_1\tilde{\theta}_1^2-\frac{1}{2}\sigma_2\tilde{\theta}_2^2+\frac{z_2 z_3}{{k_{b2}}^2-{z_2}^2}+C_2\end{aligned} \tag{31}$$

Where $C_2=\sum_{j=1}^{2}\left[\frac{{a_j}^2}{2}+\frac{\bar{d}_j^2}{2}+\frac{\bar{\tau}_j^2}{2}+\frac{1}{2}\sigma_j{\theta_j}^2\right]$.

Step i $(i=3,\cdots,n-1)$: Select the following barrier Lyapunov function

$$V_i = V_{i-1} + \frac{1}{2}\log\frac{{k_{bi}}^2}{{k_{bi}}^2 - {z_i}^2} + \frac{1}{2}\tilde{\theta}_i^2 \tag{32}$$

Where $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$, $\hat{\theta}_i$ is the estimated value of θ_i.

According to (7), it has

$$\dot{z}_i = f_i + z_{i+1} + \alpha_i + d_i - \dot{\alpha}_{i-1} \tag{33}$$

Taking the derivative of V_i yields

$$\begin{aligned}\dot{V}_i =& \dot{V}_{i-1} + \frac{z_i}{{k_{bi}}^2 - {z_i}^2}\left[f_i + z_{i+1} + \alpha_i + d_i - \dot{\alpha}_{i-1}\right] \\ &- \tilde{\theta}_i\dot{\hat{\theta}}_i\end{aligned} \tag{34}$$

By using Lemma 4, it has

$$\frac{z_i}{{k_{bi}}^2 - {z_i}^2}d_i \le \frac{{z_i}^2}{2({k_{bi}}^2 - {z_i}^2)^2} + \frac{\bar{d}_i^2}{2} \tag{35}$$

Substituting it into (34) yields

$$\begin{aligned}\dot{V}_i \le& \dot{V}_{i-1} + \frac{z_i}{{k_{bi}}^2 - {z_i}^2}\left[F_i(Z_i) + z_{i+1} + \alpha_i\right] \\ &+ \frac{\bar{d}_i^2}{2} - \tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{z_{i-1}z_i}{{k_{bi-1}}^2 - {z_{i-1}}^2}\end{aligned} \tag{36}$$

Where $F_i(Z_i) = f_i + \frac{z_i}{2({k_{bi}}^2 - {z_i}^2)} - \dot{\alpha}_{i-1} + \frac{{k_{bi}}^2 - {z_i}^2}{{k_{bi-1}}^2 - {z_{i-1}}^2}z_{i-1}$, $Z_i = \left[\bar{x}_i^T, \bar{y}_{di}^T, \bar{\theta}_{i-1}, \rho\right]$, $\bar{y}_{di} = \left[y_d, \dot{y}_d, ..., {y_d}^{(i)}\right]^T$, $\bar{\theta}_{i-1} = \left[\theta_1, ..., \theta_{i-1}\right]^T$.

Similarly, using RBFNN to approach $F_i(Z_i)$:

$$F_i(Z_i) = {W_i^*}^T S_i(Z_i) + \tau_i(Z_i) \tag{37}$$

By using Lemma 4 and Assumption 1, it has

$$\begin{aligned}\frac{z_i}{{k_{bi}}^2 - {z_i}^2}F_i(Z_i) \le& \frac{{z_i}^2\theta_i {S_i}^T S_i}{2{a_i}^2({k_{bi}}^2 - {z_i}^2)^2} + \frac{{a_i}^2}{2} \\ &+ \frac{{z_i}^2}{2({k_{bi}}^2 - {z_i}^2)^2} + \frac{\bar{\tau}_i^2}{2}\end{aligned} \tag{38}$$

Where $\theta_i = \|{W_i}^*\|^2$, $a_i > 0$ is the design parameter. Then, combine (38) with (36) yields

$$\begin{aligned}\dot{V}_i \le& \dot{V}_{i-1} + \frac{z_i}{{k_{bi}}^2 - {z_i}^2}\left[\frac{z_i\hat{\theta}_i {S_i}^T S_i}{2{a_i}^2({k_{bi}}^2 - {z_i}^2)}\right. \\ &\left. + \frac{z_i}{2({k_{bi}}^2 - {z_i}^2)} + z_{i+1} + \alpha_i\right] + \frac{{a_i}^2}{2} + \frac{\bar{\tau}_i^2}{2} + \frac{\bar{d}_i^2}{2} \\ &- \frac{z_{i-1}z_i}{{k_{bi-1}}^2 - {z_{i-1}}^2} + \tilde{\theta}_i\left[\frac{{z_i}^2 {S_i}^T S_i}{2{a_i}^2({k_{bi}}^2 - {z_i}^2)^2} - \dot{\hat{\theta}}_i\right]\end{aligned} \tag{39}$$

Design virtual control signal and adaptive law as follows

$$\alpha_{\mathrm{i}} = -\lambda_i z_i - \frac{z_i}{2({k_{bi}}^2 - {z_i}^2)} - \frac{z_i\hat{\theta}_i {S_{\mathrm{i}}}^T S_{\mathrm{i}}}{2{a_i}^2({k_{bi}}^2 - {z_i}^2)} \tag{40}$$

$$\dot{\hat{\theta}}_i = -\sigma_i\hat{\theta}_i + \frac{{z_i}^2 {S_{\mathrm{i}}}^T S_{\mathrm{i}}}{2{a_i}^2({k_{bi}}^2 - {z_i}^2)^2} \tag{41}$$

Where $\lambda_i > 0$, $\sigma_i > 0$ are design parameters, then $\dot{V}_i$ can be obtained

$$\begin{aligned}\dot{V}_i \le& -\lambda_1\frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{i}\lambda_j\frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ &- \frac{1}{2}\sum_{j=1}^{i}\sigma_j\tilde{\theta}_j^2 + \frac{z_i z_{i+1}}{{k_{bi}}^2 - {z_i}^2} + C_i\end{aligned} \tag{42}$$

Where $C_i = \sum_{j=1}^{i}\left[\frac{{a_j}^2}{2} + \frac{\bar{d}_j^2}{2} + \frac{\bar{\tau}_j^2}{2} + \frac{1}{2}\sigma_j{\theta_j}^2\right]$.

Step n: Select the obstacle Lyapunov function as follows

$$V_n = V_{n-1} + \frac{1}{2}\log\frac{{k_{bn}}^2}{{k_{bn}}^2 - {z_n}^2} + \frac{1}{2}\tilde{\theta}_n^2 \tag{43}$$

Where $\tilde{\theta}_n = \theta_n - \hat{\theta}_n$, $\hat{\theta}_n$ is the estimated value of θ_n.

By using (7), there has

$$\dot{z}_n = f_n + u + d_n - \dot{\alpha}_{n-1} \tag{44}$$

Taking the derivative of V_n yields

$$\begin{aligned}\dot{V}_n =& \dot{V}_{n-1} + \frac{z_n}{{k_{bn}}^2 - {z_n}^2}\left[f_n + u + d_i - \dot{\alpha}_{n-1}\right] \\ &- \tilde{\theta}_n\dot{\hat{\theta}}_n\end{aligned} \tag{45}$$

According to Lemma 4 and Assumption 1, the following inequality holds

$$\frac{z_n}{{k_{bn}}^2 - {z_n}^2}d_n \le \frac{{z_n}^2}{2({k_{bn}}^2 - {z_n}^2)^2} + \frac{\bar{d}_n^2}{2} \tag{46}$$

Substituting it into (45), it has

$$\begin{aligned}\dot{V}_n \le& \dot{V}_{n-1} + \frac{z_n}{{k_{bn}}^2 - {z_n}^2}\left[F_n(Z_n) + u\right] \\ &+ \frac{\bar{d}_n^2}{2} - \tilde{\theta}_n\dot{\hat{\theta}}_n - \frac{z_{n-1}z_n}{{k_{bn-1}}^2 - {z_{n-1}}^2}\end{aligned} \tag{47}$$

Where $F_n = f_n + \frac{z_n}{2({k_{bn}}^2 - {z_n}^2)} - \dot{\alpha}_{n-1} + \frac{{k_{bn}}^2 - {z_n}^2}{{k_{bn-1}}^2 - {z_{n-1}}^2}z_{n-1}$, $Z_n = \left[\bar{x}_n^T, \bar{y}_{dn}^T, \bar{\theta}_{n-1}, \rho\right]$, $\bar{y}_{dn} = \left[y_d, \dot{y}_d, ..., {y_d}^{(n)}\right]^T$, $\bar{\theta}_{n-1} = \left[\theta_1, ..., \theta_{n-1}\right]^T$.

Similarly

$$F_n(Z_n) = {W_n^*}^T S_n(Z_n) + \tau_n(Z_n) \tag{48}$$

By Lemma 4, it can be obtained

$$\begin{aligned}\frac{z_n}{{k_{bn}}^2 - {z_n}^2}F_n(Z_n) \le& \frac{{z_n}^2\theta_n {S_n}^T S_n}{2{a_n}^2({k_{bn}}^2 - {z_n}^2)^2} + \frac{{a_n}^2}{2} \\ &+ \frac{{z_n}^2}{2({k_{bn}}^2 - {z_n}^2)^2} + \frac{\bar{\tau}_n^2}{2}\end{aligned} \tag{49}$$

Where $\theta_n = \|{W_n}^*\|^2$, $a_n > 0$, a_n is the design parameter. Then, combining (49) with (47), it yields

$$\begin{aligned}\dot{V}_n \le& \dot{V}_{n-1} + \frac{z_n}{{k_{bn}}^2 - {z_n}^2}\left[\frac{z_n\hat{\theta}_n {S_n}^T S_n}{2{a_n}^2({k_{bn}}^2 - {z_n}^2)}\right. \\ &\left. + \frac{z_n}{2({k_{bn}}^2 - {z_n}^2)} + u\right] + \frac{{a_n}^2}{2} + \frac{\bar{\tau}_n^2}{2} + \frac{\bar{d}_n^2}{2} - \\ &\frac{z_n z_{n-1}}{{k_{bn}}^2 - {z_n}^2} + \tilde{\theta}_n\left[\frac{z_n {S_n}^T S_n}{2{a_n}^2({k_{bn}}^2 - {z_n}^2)^2} - \dot{\hat{\theta}}_n\right]\end{aligned} \tag{50}$$

Based on the preceding information, design virtual controller and adaptive law as follows

$$\alpha_{\mathrm{n}} = -\lambda_n z_n - \frac{z_n}{2({k_{bn}}^2 - {z_n}^2)} - \frac{z_n\hat{\theta}_n {S_{\mathrm{n}}}^T S_{\mathrm{n}}}{2{a_n}^2({k_b}^2 - {z_n}^2)} \tag{51}$$

$$\dot{\hat{\theta}}_n = -\sigma_n\hat{\theta}_{\mathrm{n}} + \frac{{z_n}^2 {S_{\mathrm{n}}}^T S_{\mathrm{n}}}{2{a_n}^2({k_{bn}}^2 - {z_n}^2)^2} \tag{52}$$

Where $\lambda_n > 0$, $\sigma_n > 0$ are design parameters, then $\dot{V}_n$ can be rewritten as

$$\begin{aligned}\dot{V}_n \leq & -\lambda_1 \frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{n} \lambda_j \frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ & - \frac{1}{2} \sum_{j=1}^{n} \sigma_j \tilde{\theta}_j^2 + \frac{z_n}{{k_{bn}}^2 - {z_n}^2}(u - \alpha_n) + C_n\end{aligned} \tag{53}$$

Where $C_n = \sum_{j=1}^{n} \left[\frac{{a_j}^2}{2} + \frac{\bar{d}_j^2}{2} + \frac{\bar{\tau}_j^2}{2} + \frac{1}{2}\sigma_j {\theta_j}^2 \right]$.

B. Event-triggered control

The relative threshold event-triggered mechanism [34] is as follows

$$\begin{aligned}\psi(t) = & -(1+\xi) \left[\alpha_n \tanh\left(\frac{z_n \alpha_n}{\varepsilon({k_{bn}}^2 - {z_n}^2)} \right) + \right. \\ & \left. \bar{m}_1 \tanh\left(\frac{z_n \bar{m}_1}{\varepsilon({k_{bn}}^2 - {z_n}^2)} \right) \right] \\ u(t) = & \psi(t_k), \forall t \in [t_k, t_{k+1}) \\ t_{k+1} = & \inf \left\{ |\chi(t)| \geq \xi \left| u(t) \right| + m_1 \right\}\end{aligned} \tag{54}$$

Where ξ, ε, $\bar{m}_1$, m_1 are positive design parameters, $0 < \xi < 1$ and $\bar{m}_1 > \frac{m_1}{1-\xi}$. $\chi(t) = \psi(t) - u(t)$ is the related measurement error.

C. Stability analysis

Theorem 1. On the premise of assumptions 1-3, a class of nonlinear uncertain system (1) with full-state constraints, unknown time-varying disturbances and prescribed performance is considered, and the control laws and adaptive laws shown in (1), (29), (30), (40), (41), (51) and (52) are designed. Under the action of the event-triggered mechanism (54), the following conclusions are established by selecting appropriate design parameters:

(1) All signals in the closed-loop system are uniformly and ultimately bounded, and the system error meets the preset requirements.

(2) All states in the system will be not violate the predefined constraint interval.

(3) Event-triggered interval time meets $t_{k+1} - t_k \geq t^*$, that is, the Zeno behavior will not happen.

Proof: (1) According to the following formula

$$\psi(t) = \left[1 + \xi\beta_1(t)\right] u(t) + m_1\beta_2(t), \forall t \in [t_k, t_{k+1}) \tag{55}$$

Where $|\beta_1(t)| \leq 1$, $|\beta_2(t)| \leq 1$ are time-varying parameters, we can get

$$u(t) = \frac{\psi(t) - m_1\beta_2(t)}{1 + \xi\beta_1(t)} \tag{56}$$

Substituting (56) into (53) yields

$$\begin{aligned}\dot{V}_n \leq & -\lambda_1 \frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{n} \lambda_j \frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ & - \frac{1}{2} \sum_{j=1}^{n} \sigma_j \tilde{\theta}_j^2 + \frac{z_n}{{k_{bn}}^2 - {z_n}^2} \left[\frac{\psi(t)}{1 + \xi\beta_1(t)} \right] \\ & - \frac{z_n}{{k_{bn}}^2 - {z_n}^2} \left[\frac{m_1\beta_2(t)}{1 + \xi\beta_1(t)} \right] \\ & + \left| \frac{z_n \alpha_n}{{k_{bn}}^2 - {z_n}^2} \right| + C_n\end{aligned} \tag{57}$$

Combining $|\beta_1(t)| \leq 1$ with $\psi(t)$ yields

$$\begin{aligned}& \frac{z_n}{{k_{bn}}^2 - {z_n}^2} \left[\frac{\psi(t)}{1 + \xi\beta_1(t)} \right] \\ & \leq - \frac{z_n \alpha_n}{{k_{bn}}^2 - {z_n}^2} \tanh\left(\frac{z_n \alpha_n}{\varepsilon({k_{bn}}^2 - {z_n}^2)} \right) \\ & - \frac{z_n \bar{m}_1}{{k_{bn}}^2 - {z_n}^2} \tanh\left(\frac{z_n \bar{m}_1}{\varepsilon({k_{bn}}^2 - {z_n}^2)} \right)\end{aligned} \tag{58}$$

Based on Lemma 2, it has

$$\begin{aligned}\dot{V}_n \leq & -\lambda_1 \frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{n} \lambda_j \frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ & - \frac{1}{2} \sum_{j=1}^{n} \sigma_j \tilde{\theta}_j^2 + 0.2785\varepsilon \\ & - \frac{z_n \bar{m}_1}{{k_{bn}}^2 - {z_n}^2} \tanh\left(\frac{z_n \bar{m}_1}{\varepsilon({k_{bn}}^2 - {z_n}^2)} \right) \\ & - \frac{z_n}{{k_{bn}}^2 - {z_n}^2} \left[\frac{m_1\beta_2(t)}{1 + \xi\beta_1(t)} \right] + C_n \\ \leq & \lambda_1 \frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{n} \lambda_j \frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ & - \frac{1}{2} \sum_{j=1}^{n} \sigma_j \tilde{\theta}_j^2 + 0.557\varepsilon - \left| \frac{z_n \bar{m}_1}{{k_{bn}}^2 - {z_n}^2} \right| \\ & + \left| \frac{z_n m_1}{({k_{bn}}^2 - {z_n}^2)(1-\xi)} \right| + C_n\end{aligned} \tag{59}$$

By using $\bar{m}_1 > \frac{m_1}{1-\xi}$, it has

$$\begin{aligned}\dot{V}_n \leq & -\lambda_1 \frac{{\eta_1}^2}{{k_{b1}}^2 - {\eta_1}^2} - \sum_{j=2}^{n} \lambda_j \frac{{z_j}^2}{{k_{bj}}^2 - {z_j}^2} \\ & - \frac{1}{2} \sum_{j=1}^{n} \sigma_j \tilde{\theta}_j^2 + 0.557\varepsilon + C_n\end{aligned} \tag{60}$$

Since $\log \frac{{k_b}^2}{{k_b}^2 - z^2} < \frac{z^2}{{k_b}^2 - z^2}$ for $|z| < k_b$, $\dot{V}_n$ can finally be rewritten as

$$\dot{V}_n \leq -CV_n + D \tag{61}$$

Where $C = \min\left\{2\lambda_j, \sigma_j, j = 1, ..., n\right\}, D = 0.557\varepsilon + C_n$.

Furthermore, (61) can be solved by Lemma 3 as follows

$$V_n \leq V_n(0)e^{-Ct} + \frac{D}{C} \tag{62}$$

According to the definition of V_n, there has

$$|z_j| \leq k_{bj}\sqrt{1 - e^{-2[V_n(0)e^{-Ct} + D/C]}} \tag{63}$$

The above results show that system signals are bounded, and the tracking error can be converged to the prescribed range by choosing appropriate design parameters. In addition, in view of $\tilde{\theta}_j = \theta_j - \hat{\theta}_j$, it can be concluded that $\hat{\theta}_j$ is bounded.

(2) In view of $|x_1| < |z_1| + |y_d| < k_{b1} + A_1$ and $k_{b1} = k_{c1} - A_1$, we can get $|x_1| < k_{c1}$. Because α_1 is composed of bounded signals, there is a constant A_2 that makes $|\alpha_1| < A_2$, combining $|x_2| = |z_2 + \alpha_1|$, it can be concluded that $|x_2| < k_{b2} + A_2$. Let $k_{b2} = k_{c2} - A_2$, then $|x_2| < k_{c2}$. Likewise, $|x_i| < k_{ci}, i = 3, ..., n$ can be verified.

(3) From $\chi(t) = \psi(t) - u(t)$, it has

$$\frac{d}{dt}\left|\chi(t)\right| = sign(\chi(t))\dot{\chi}(t) \leq \left|\dot{\psi}(t)\right| \tag{64}$$

Based on (55), $\dot{\psi}(t)$ can be verified to be continuous. Therefore, when ϖ is a constant, $\left|\dot{\psi}(t)\right| \leq \varpi$ holds. In addition, $\chi(t_k) = 0$ and $\lim_{t \to t_{k+1}} \chi(t) = \xi |u(t)| + m_1$, the execution interval t^* is required to meet $t^* \geq \frac{\xi|u(t)|+m_1}{\varpi}$, so the Zeno-behavior dose not happen.

Remark 1. All signals of the closed-loop system are bounded and all states meet the predefined constraint interval on the basis of the above proof process. The relative threshold event-triggered mechanism can not only lower the triggering times, but also maintain the expected performance.

IV. SIMULATION EXAMPLES

In order to verify the effectiveness of the control strategy, this section takes the single-link flexible manipulator in [35] as the simulation object. and its system dynamics model is described as follows

$$\begin{cases} J\ddot{q} + B\dot{q} + MgL\sin(q) = u + d \\ y = q \end{cases} \tag{65}$$

Defining the system state variables as $x_1 = q$, $x_2 = \dot{q}$, then (65) can be rewritten as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{1}{J}\left(u + d - Bx_2 - MgL\sin(x_1)\right) \\ y = x_1 \end{cases} \tag{66}$$

Where $x_1 = q$, $x_2 = \dot{q}$ represent joint angle and angular respectively, J represents joint moment of inertia, M represents the mass of the manipulator, g represents gravity acceleration, and L is the length of the connecting rod. The parameters of the manipulator are set as follows: $J = 1$, $B = 1$, $MgL = 2$, $d = 0.01\sin(t)$. The initial values are set to $[x_1(0), x_2(0)]^{\mathrm{T}} = [0.01, 0.01]^{\mathrm{T}}$, $[\theta_1(0), \theta_2(0)]^{\mathrm{T}} = [0, 0.2]^{\mathrm{T}}$. The system states are $|x_1| < 1.2$ and $|x_2| < 1.4$.

For certifying the tracking performance of the system, the reference signal is chosen as $y_d = \sin(t)$. Select Gaussian function $S_i(Z_i) = \exp(-\frac{(Z_i-\upsilon_i)^2}{2})$, $i = 1, 2$, $\upsilon_i = [-5, 5]$ as radial basis function. The prescribed performance function is set to $\rho(t) = (1 - 0.03)e^{-2t} + 0.03$. Other relevant design parameters are set as $\lambda_1 = 30$, $\lambda_2 = 30$, $a_1 = 4$, $a_2 = 6$, $\sigma_1 = 6$, $\sigma_2 = 4$, $k_{b1} = 0.5$, $k_{b2} = 1.8$, $m_1 = 0.5$, $\bar{m}_1 = 1.5$, $\xi = 0.5$, $\varepsilon = 11$.

The simulation results are shown in Figure 1- Figure 7. Figure 1 is the tracking curve of the system response. We note that the system has good tracking performance and the system state x_1 meets the constraint conditions. Fig. 2 shows the system state x_2, which also does not violate the constraint conditions. Fig. 3 shows the designed adaptive law, which shows that θ_1, θ_2 are bounded. Fig. 4 is the error curve without prescribed performance control. Compared with the tracking error with prescribed performance shown in Figure 5, it can be noted that the prescribed performance function effectively reduces the tracking error of the system and improves the transient performance and steady performance of the system. Fig. 6 shows the control input and the event-triggered control input, which shows that the input signal is bounded. In fig. 7, the total triggering times of the event-triggered mechanism in 20s are only 388 times. Contrast that with the traditional time-triggered mechanism, communication resources are effectively saved on account of the event triggering mechanism, and the Zeno-behavior will not occur.

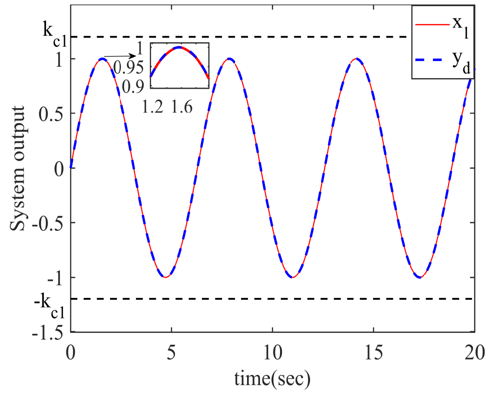

Fig. 1. Tracking curve.

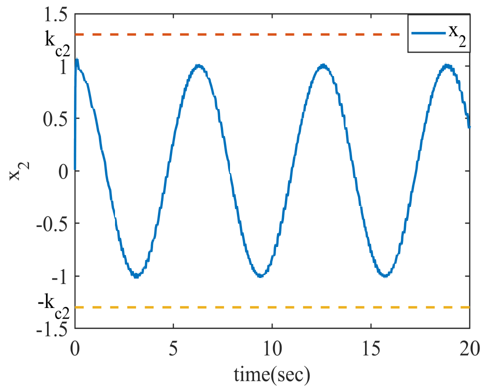

Fig. 2. Curve of system state x_2.

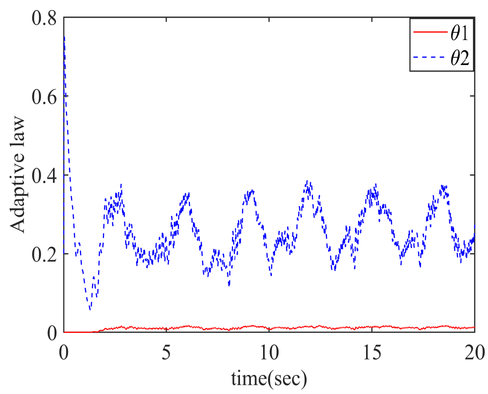

Fig. 3. Adaptive law .

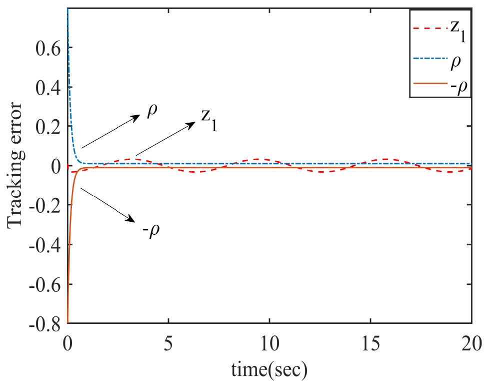

Fig. 4. Tracking error (no prescribed performance).

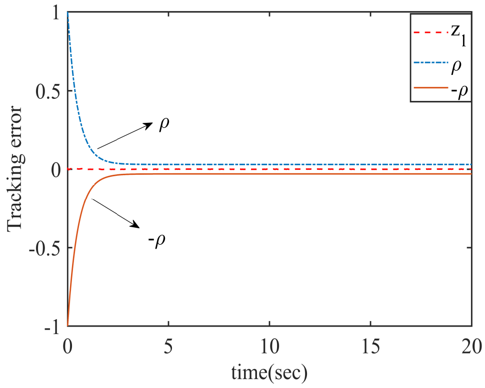

Fig. 5. Tracking error (prescribed performance).

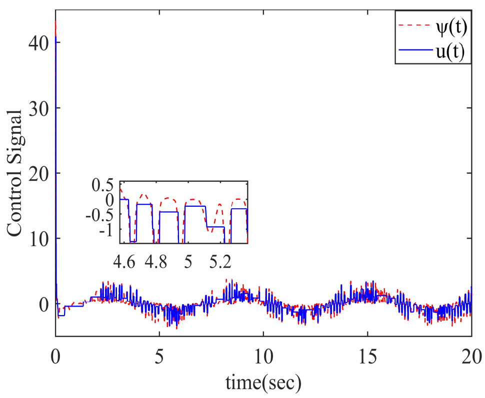

Fig. 6. Control Signals.

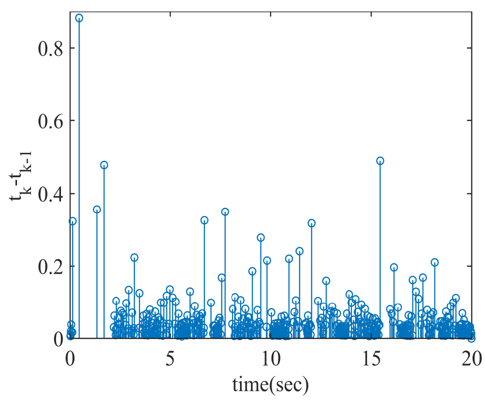

Fig. 7. Trigger time interval.

V. CONCLUSION

In this paper, a prescribed performance adaptive event-triggered control strategy is proposed for a class of uncertain nonlinear systems with state constraints and unknown time-varying disturbances. Compared with other existing control schemes, it not only enables the system to have better transient and steady-state performance, but also ensures that all states of the system are bounded and do not violate predetermined state intervals. The introduction of the relative threshold event-triggered mechanism effectively reduces the communication burden and greatly saves communication resources, and the controller has no Zeno-behavior.

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