Event-Triggered Adaptive Prescribed Performance Control of Uncertain Nonlinear Systems

Haibo Xu, Xinyu Ouyang, Nannan Zhao and Yiqin Zhou

***Abstract*—An event-triggered based on prescribed performance control (PPC) for the tracking control problem of strict-feedback uncertain nonlinear systems with input saturation constraint is studied. First, a smooth nonlinear function is introduced to approximate the saturation function. Secondly, the PPC design process of a class of uncertain nonlinear systems and a new error transformation function are designed to guarantee the output of the system does not violate the set constraints of the preset functions. Thirdly, an event-triggered based on adaptive PPC for a class of uncertain nonlinear systems is implemented. It makes all closed-loop signals in the system uniformly ultimately bounded (UUB). Finally, an example is given to demonstrate the effectiveness of the proposed method.**

***Index Terms*—Nonlinear systems, event-triggered control (ETC), prescribed performance control (PPC), unknown control direction**

I. Introduction

In the past several decades, adaptive control based on backstepping technique has been one of the most commonly used nonlinear system design methods. This method provides a general iterative construction tool for designing controllers, and some significant control schemes have been developed [1]–[6]. Since the nonlinear systems contain unknown terms, neural networks [7]–[10] and fuzzy logic systems [11]–[14] have been widely applied to the control design for uncertain nonlinear systems.

Recently, a new method called prescribed performance control (PPC) has become a research hotspot. In practical control systems, PPC not only guarantees the stability of the nonlinear system but also guarantees the transient and steady state operation of the system [15]–[18]. For the strict-feedback nonlinear system with uncertain multi-input and multi-output, in [15], Malek et al. designed an adaptive tracking controller to make the tracking error converge to its predefined boundary. In [16], an adaptive fuzzy controller with prescribed constraint for a class of nonlinear strictly feedback nonlinear systems has been designed by using fuzzy approximation. In [17], Zhang et al. realized the control of the nonlinear feedback system with unknown direction by using the preset performance, rather than using the neural/fuzzy system to approximate the results, which greatly reduced the computational complexity.

Manuscript received March 26, 2021; revised July 26, 2021. This work is supported in part by the Scientific Research Fund of Liaoning Provincial Education Department of China (Grant Nos. 2019LNJC11 and 2019LNJC13).

Haibo xu is a postgraduate of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, Liaoning, CO114051, China. (e-mail: 502679740@qq.com)

Xinyu Ouyang is a professor of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, Liaoning, CO 114051, China. (corresponding author: e-mail: 13392862@qq.com).

Nannan Zhao is an associate professor of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, Liaoning, CO 114051, China. (e-mail: 723306003@qq.com)

Yiqin Zhou is a postgraduate of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, Liaoning, CO114051, China. (e-mail: 1179820057@qq.com)

Remarkably, data transmission is accomplished through periodic sampling in the framework of classical sample-data control. Unfortunately, the network resources are limited, and the periodic transmission scheme causes a large amount of communication resources waste and increases the operating cost of the system. Therefore, a new control approach called event trigger control (ETC) [19]–[23] has been proposed to solve the above problems. ETC has made significant progress in recent years [24]–[27]. In [24], Xing et al. designed new design methods based on fixed threshold strategy, relative threshold strategy and switching threshold strategy. In [26], the results of [24] were extended to the event triggering control problem of uncertain nonlinear systems with actuator failure.

In addition, the control problem of saturated nonlinear systems has been taken concerned by researchers [28]–[31]. In [31], Wang et al. designed an adaptive tracking controller for a class of pure-feedback stochastic nonlinear systems with input saturation. They solved the problem of non-differential saturation nonlinearity by using a smooth nonlinear function.

Inspired by the work in [16], [24] and [31], we design an event-triggered with fixed threshold strategy based on adaptive PPC for a class of uncertain nonlinear systems with input saturation. The main contributions of this work are summarized as follows:

(1) A new error transformation function is used for the first time to generalize an adaptive tracking control scheme for a class of strict-feedback uncertain nonlinear systems with input saturation constraints, where the problems of PPC and ETC are considered simultaneously.

(2) Compared with PPC results in [16], this paper extends the conclusion to strict feedback systems with unknown disturbances and input saturation.

The rest of this paper is as follows: Section II introduces the unknown nonlinear system function, saturation function, new error transformation function and some preliminary contents. In Section III, backstepping technology is used to design the fixed threshold policy event-triggered adaptive controller. The simulation studies are carried out in Section IV to verify the effectiveness of the proposed method. Finally, Section V concludes the paper.

II. System descriptions and basic knowledge

Consider a single-input and single-output (SISO) strick-feedback nonlinear system with unknown control directions and unknown disturbances by the form

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i) + h_i(\bar{x}_i)x_{i+1}(t) + \lambda_i(t) \\ \dot{x}_n = f_n(\bar{x}_n) + h_n(\bar{x}_n)u(t) + \lambda_n(t) \\ y \ = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \cdots, x_i]^T \in \mathbb{R}^i$ $(i = 1, 2, \cdots, n)$ indicates the system state vector, $y \in \mathbb{R}$ is the system output. $f_i(\cdot) : \mathbb{R}^i \to \mathbb{R}$ and $h_i(\cdot) : \mathbb{R}^i \to \mathbb{R}$ are unknown smooth functions, $\lambda_i(t)$ show the unknown perturbation and $|\lambda_i(t)| < \bar{\lambda}_i, i = 1, 2, \cdots, n$, where $\bar{\lambda}_i$ are unknown positive constant, and $u(t)$ denotes the actual control input subject to stochastic saturation nonlinearity, and $S(v)$ represents the actuator saturation nonlinearity operator with unknown constants $u_{\max} > 0$ and $u_{\min} < 0$, described by

$$u(t) = S(v) = \begin{cases} u_{\max}, v \geq u_{\max} \\ v, \qquad u_{\min} < v < u_{\max} \\ u_{\min}, v \leq u_{\min} \end{cases} \tag{2}$$

where v is the input signal of the saturation nonlinearity system. From (2), when $v(t) = u_{max}$ or $v(t) = u_{min}$, there exist two sharp corners. In order to construct control input signal directly by the backstepping technique. As in [32], $S(v)$ can be approximated by the sum of a smooth function $G(v)$ and an approximation error $g(v)$, where $G(v)$ can be defined as

$$G(v) = \begin{cases} u_{\max} * \tanh(\frac{v}{u_{\max}}), v \geq 0 \\ u_{\min} * \tanh(\frac{v}{u_{\min}}), v < 0 \end{cases} = \begin{cases} u_{\max} * \dfrac{e^{\frac{v}{u_{\max}}} - e^{\frac{-v}{u_{\max}}}}{e^{\frac{v}{u_{\max}}} + e^{\frac{-v}{u_{\max}}}}, v \geq 0 \\ u_{\min} * \dfrac{e^{\frac{v}{u_{\min}}} - e^{\frac{-v}{u_{\min}}}}{e^{\frac{v}{u_{\min}}} + e^{\frac{-v}{u_{\min}}}}, v < 0 \end{cases} \tag{3}$$

Then, $S(v)$ in (2) can be given by:

$$u = S(v) = G(v) + g(v) = G_\sigma(v)v + g(v) \tag{4}$$

where $G_\sigma(v) = (\partial G(v)/\partial v)|_{v = v_\sigma}$, and $v_\sigma = \sigma v$, $(0 < \sigma < 1)$. In addition, according to $g(v) = S(v) - G(v)$ is a bounded function, the following formula is established

$$\begin{aligned} |g(v)| &= |S(v) - G(v)| \\ &\leq \max\{u_{\max}(1 - \tanh(1)), \\ &u_{\min}(1 - \tanh(1))\} \\ &= D \end{aligned} \tag{5}$$

Substituting (4) into (1) results in

$$\begin{aligned} \dot{x}_i &= f_i(\bar{x}_i) + h_i(\bar{x}_i)x_{i+1}(t) + \lambda_i(t) \\ \dot{x}_n &= f_n(\bar{x}_n) + h_n(\bar{x}_n)G_\sigma v + h_n(\bar{x}_n)g(v) \\ &\quad + \lambda_n(t) \end{aligned} \tag{6}$$

Assumption 1: For the functions $h_i (1 \leq i \leq n)$, there exist unknown positive constants b and b_M such that

$$0 < b \leq |h_i| \leq b_M < \infty \tag{7}$$

Apparently, h_i are strictly either positive or negative. Without loss of generality, it is further assumed that $0 < b \leq h_i \leq b_M$.

Assumption 2: The function G_σ in (6) is bounded by

$$0 < G_m \leq G_\sigma < 1 \tag{8}$$

where G_m is an unknown positive constant.

Remark 1: As stated in [32], the limitation in (8) was recommended. In many physical processes and systems, the actual control input signal v must be finite , so Assumption 2 is legitimate.

Remark 2: According to Assumptions 1 and 2, it produces $0 < b_m \leq h_i$, $0 < b_m \leq h_i G_\sigma$ $(i = 1, 2, \ldots, n-1)$, where $b_m = \min\{b, bG_m\}$.

Lemma 1: [31] The desired signal $y_r(t)$ and $\dot{y_r}(t)$, $\ddot{y_r}(t)$, $\cdots, {y_r}^{(n)}(t)$ (n $\in R^+$) are continuous, bounded and known.

In this note, the fuzzy logic system is applied to estimate the function $f(x)$ defined on some compact sets. The fuzzy logic system can be written as

$$y(x) = W^T\psi(x) \tag{9}$$

where W is a collection of points for a fuzzy membership function, $\psi(x)$ is the set of maximum operation of fuzzy set. If all memberships are chosen as Gaussian functions, the following lemma holds.

Lemma 2: [33] Let the continuous function $f(x)$ defined on a compact set Ω. Then, for any given positive constant $\varepsilon > 0$, there exists a fuzzy logic system (9) such that

$$\sup_{x\in\Omega} \left| f(x) - W^T\psi(x) \right| \leq \varepsilon$$

Lemma 3: [34] For $\forall(x, y) \in R^2$, we have:

$$xy \leq \frac{\beta^p}{p}|x|^p + \frac{1}{q\beta^q}|y|^q \tag{10}$$

where the positive constants $\beta > 0$, $p > 1$, $q > 1$, furthermore, p and q satisfy $(p-1)(q-1) = 1$.

III. Controller Design

A. Prescribed performance control

The state errors are defined as follows:

$$\begin{aligned} z_1 &= x_1 - y_r, \\ z_i &= x_i - \alpha_{i-1}, \quad i = 2, 3, \cdots, n \end{aligned} \tag{11}$$

where y_r is the desired trajectory and $\alpha_i (i = 2, \ldots, n)$ denote virtual control law, which are used to stabilize each backstepping design step. In order to accomplish prescribed performance control (PPC) for each tracking trajectory error z_i, the convergence domain function is defined as

$$\varrho_1 = (\varrho_0 - \varrho_\infty)e^{-\xi t} + \varrho_\infty, \tag{12}$$

with $\varrho_0 > \varrho_\infty$, where ϱ_0 describing the initial value, ϱ_∞ is the maximum allowed steady state error and ξ representing minimum speed of convergence, all of them are predefined positive constants. In order to stabilize (1) and guarantee $|z_i(0)| < |\varrho_0|$ can constrained the transient and steady state bounds for the output tracking error z_i, the new error transformations is expressed as

$$\eta_1 = \ln(\frac{\varrho_1 + z_1}{\varrho_1 - z_1}) \tag{13}$$

Remark 3: The hyperbolic tangent function $tanh^{-1}(x) = \frac{1}{2}\ln(1 + x/1 - x)$ is used to design the new error transformations η_1. According to the properties of $tanh^{-1}(\cdot)$, if ${\eta_1}^2(t)$ is bounded, then inequality $|z_1(t)| < \varrho_1(t)$ holds. The tracking error z_1 is constrained by the prescribed performance function ϱ_1, and the transient and steady state performance can be guaranteed with the desired trajectory $y_r(t)$. This also means that the design of the Lyapunov function in the form of (18) is reasonable.
The virtual control law α_1 is defined as

$$\alpha_1{=}-\frac{\eta_1}{\phi_1}(a_1 + \frac{1}{2} + \frac{1}{2C_1^2}\hat{\theta}\psi_1^T(Z_1)\psi_1(Z_1)) \tag{14}$$

where $Z_1 = [x_1, y_r, \dot{y}_r, \varrho_1, \dot{\varrho}_1]$, α_1 is the function of $[x_1, \hat{\theta}, y_r, \dot{y}_r, \varrho_1, \dot{\varrho}_1]$

$$\begin{aligned} \alpha_i &= -(a_i + \frac{1}{2})z_i - \frac{1}{2C_i^2}z_i\hat{\theta}\psi_i^T(Z_i)\psi_i(Z_i) \\ \alpha_n &= -(a_n + \frac{1}{2d^2})z_n - \frac{1}{2C_n^2}z_n\hat{\theta}\psi_n^T(Z_n)\psi_n(Z_n) \end{aligned} \tag{15}$$

where a_i, $C_i (i = 1, 2, ..., n)$ and d are positive design constants, $Z_i = [\bar{x}_n, \hat{\theta}, y_r, \dot{y}_r \cdots y_r^{(i)}, \varrho_1, \dot{\varrho}_1 \cdots \varrho_1^{(i)}]$, α_i are the functions of $[\bar{x}_n, \hat{\theta}, y_r, \dot{y}_r \cdots y_r^{(i)}, \varrho_1, \dot{\varrho}_1 \cdots \varrho_1^{(i)}]$, $\hat{\theta}$ is the estimate value of the adaptive law θ, which is specified as

$$\theta{=}\max_{1\le i\le n}\left\{\frac{\|W_i^*\|^2}{b_m}\right\} \tag{16}$$

$\hat{\theta}$ can be updated by

$$\dot{\hat{\theta}} = \frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 + \sum_{i=2}^{n}\frac{\epsilon}{2C_i^2}z_i^2\psi_i^T\psi_i - \delta\hat{\theta} \tag{17}$$

where ϵ and δ are positive design constants.

B. Event-triggered controller design

In this subsection, an adaptive fuzzy control design procedure based on backstepping technique will be proposed. Furthermore, an event-triggered adaptive controller will be presented.

Step 1: A positive definite Lyapunov is defined as follows:

$$V_1 = \frac{1}{2}\eta_1^2 + \frac{b_m}{2\epsilon}\tilde{\theta}^2 \tag{18}$$

By combining (6), (13), (14) and (17), the derivative of $V_1(t)$ can be obtained

$$\dot{V}_1 = \eta_1\phi_1(f_1 + h_1x_2 + \lambda_1 - \dot{y}_r - \frac{\dot{\varrho}_1 z_1}{\varrho_1}) - \frac{b_m}{\epsilon}\tilde{\theta}\dot{\hat{\theta}} \tag{19}$$

Based on Lemma 3, it is not hard to obtain that $\eta_1\phi_1\lambda_1 \le \eta_1^2\phi_1^2/2 + \bar{\lambda}_1/2$. Using this inequality into (19) gives

$$\begin{aligned} \dot{V}_1 &\le \eta_1\phi_1(f_1 + h_1x_2 + \frac{\eta_1\phi_1}{2} - \dot{y}_r - \frac{\dot{\varrho}_1 z_1}{\varrho_1}) \\ &\quad + \frac{\bar{\lambda}_1^2}{2} - \frac{b_m}{\epsilon}\tilde{\theta}\dot{\hat{\theta}} \\ &\le \eta_1\phi_1 h_1 x_2 + \eta_1 F_1 + \frac{\bar{\lambda}_1^2}{2} - \frac{b_m}{\epsilon}\tilde{\theta}\dot{\hat{\theta}} \end{aligned} \tag{20}$$

where $F_1 = \phi_1[f_1 + (\eta_1\phi_1/2) - \dot{y}_r - (\dot{\varrho}_1 z_1/\varrho_1)]$. Since F_1 contains the unknown function $f(\bar{x}_1)$, F_1 cannot be directly used to construct virtual control signal α_1. By employing a fuzzy logic system $W_1^T\psi_1(Z_1)$ to approximate F_1, F_1 can be expressed as

$$F_1 = W_1^{*T}\psi_1(Z_1) + \tau_1(Z_1), \ \ |\tau_1(Z_1)| \le \bar{\varepsilon}_1 \tag{21}$$

where $\tau_1(Z_1)$ is the approximation error and $\bar{\varepsilon}_1$ is an unknown positive constant. By Lemma 3, one has

$$\begin{aligned} \eta_1 F_1 &\le \frac{b_m}{2C_1^2}\eta_1^2\frac{\left\|W_1^{*T}\right\|^2}{b_m}\psi_1^T\psi_1 + \frac{C_1^2}{2} + \frac{\eta_1^2}{2} + \frac{\bar{\varepsilon}_1^2}{2} \\ &\le \frac{b_m}{2C_1^2}\eta_1^2\theta\psi_1^T\psi_1 + \frac{C_1^2}{2} + \frac{\eta_1^2}{2} + \frac{\bar{\varepsilon}_1^2}{2} \end{aligned} \tag{22}$$

Based on (14), we can have

$$\begin{aligned} \eta_1\phi_1\alpha_1 &= -a_1h_1\eta_1^2 - \frac{\eta_1^2 h_1}{2} - \frac{\eta_1^2}{2C_1^2}h_1\hat{\theta}\psi_1^T\psi_1 \\ &\le -a_1 b_m\eta_1^2 - \frac{\eta_1^2 b_m}{2} - \frac{b_m}{2C_1^2}\eta_1^2\hat{\theta}\psi_1^T\psi_1 \end{aligned} \tag{23}$$

Then, one can deduce from (20), (22), and (23) that

$$\begin{aligned} \dot{V}_1 &\le \eta_1\phi_1 h_1 z_2 + \frac{b_m}{2C_1^2}\eta_1^2\psi_1^T\psi_1 + \frac{C_1^2}{2} + \frac{\eta_1^2}{2} + \frac{\bar{\varepsilon}_1^2}{2} \\ &\quad - a_1 b_m\eta_1^2 - \frac{\eta_1^2 b_m}{2} - \frac{b_m}{2C_1^2}\eta_1^2\hat{\theta}\psi_1^T\psi_1 \\ &\quad + \frac{\bar{\lambda}_1^2}{2} - \frac{b_m}{\epsilon}\tilde{\theta}\dot{\hat{\theta}} \\ &\le -a_1 b_m\eta_1^2 + \eta_1\phi_1 h_1 z_2 \\ &\quad + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 - \dot{\hat{\theta}}) + \Delta_1 \end{aligned} \tag{24}$$

where

$$\Delta_1 = \frac{C_1^2}{2} + \frac{\bar{\lambda}_1^2}{2} + \frac{\bar{\varepsilon}_1^2}{2}$$

Step 2: Similarly, the virtual control signal α_2 will be constructed to control the system. According to $z_2 = x_2 - \alpha_1$, we can define the Lyapunov function as follows:

$$V_2{=}V_1 + \frac{1}{2}z_2^2 \tag{25}$$

By substituting (11) and (24), we obtain the time derivative of V_2 as

$$\begin{aligned}\dot{V}_2 \leq& -a_1 b_m \eta_1^2 + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 - \dot{\hat{\theta}}) + \Delta_1 \\ &+ z_2[h_1\eta_1\phi_1 + f_2 + h_2 x_3 + \frac{z_2}{2} \\ &- \frac{\partial \alpha_1}{\partial x_1}(f_1 + h_1 x_2) + z_2(\frac{\partial \alpha_1}{\partial x_1})^2 \\ &- \sum_{k=0}^{1}\frac{\partial \alpha_1}{\partial \varrho_1^{(k)}}\varrho_1^{(k+1)} - \sum_{k=0}^{1}\frac{\partial \alpha_1}{\partial y_d^{(k)}}y_d^{(k+1)} \\ &- \frac{\partial \alpha_1}{\partial \hat{\theta}}\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 - \frac{\partial \alpha_1}{\partial \hat{\theta}}\frac{\epsilon}{2C_1^2}z_2^2\psi_2^T\psi_2 \\ &+ \frac{\partial \alpha_1}{\partial \hat{\theta}}\delta\hat{\theta}] - \frac{\partial \alpha_1}{\partial \hat{\theta}}z_2\sum_{l=3}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ &+ \frac{\bar{\lambda}_2^2}{2} + \frac{\bar{\lambda}_1^2}{4}\end{aligned} \tag{26}$$

Therefore, we can rewrite (26) as

$$\begin{aligned}\dot{V}_2 \leq& -a_1 b_m \eta_1^2 + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 - \dot{\hat{\theta}}) \\ &+ \Delta_1 - \frac{\partial \alpha_1}{\partial \hat{\theta}}z_2\sum_{l=3}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ &+ z_2(h_2 z_3 + h_2\alpha_2 + F_2) + \frac{\bar{\lambda}_2^2}{2} + \frac{\bar{\lambda}_1^2}{4}\end{aligned} \tag{27}$$

where

$$\begin{aligned}F_2 =& \eta_1 h_1\phi_1 + f_2 + \frac{z_2}{2} - \frac{\partial \alpha_1}{\partial x_1}(f_1 + h_1 x_2) \\ &+ z_2(\frac{\partial \alpha_1}{\partial x_1})^2 - \sum_{k=0}^{1}\frac{\partial \alpha_1}{\partial \varrho_1^{(k)}}\varrho_1^{(k+1)} \\ &- \sum_{k=0}^{1}\frac{\partial \alpha_1}{\partial y_d^{(k)}}y_d^{(k+1)} - \frac{\partial \alpha_1}{\partial \hat{\theta}}\frac{\epsilon}{2C_1^2}\zeta_1^2\psi_1^T\psi_1 \\ &- \frac{\partial \alpha_1}{\partial \hat{\theta}}\frac{\epsilon}{2C_1^2}z_2^2\psi_2^T\psi_2 + \frac{\partial \alpha_1}{\partial \hat{\theta}}\delta\hat{\theta}\end{aligned}$$

Similarly, based on (22), the following result holds

$$\begin{aligned}\dot{V}_2 \leq& -a_1 b_m \eta_1^2 + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 - \dot{\hat{\theta}}) \\ &+ \Delta_1 - \frac{\partial \alpha_1}{\partial \hat{\theta}}z_2\sum_{l=3}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ &+ h_2 z_2 z_3 - b_m a_2 z_2^2 - \frac{b_m}{2}z_2^2 \\ &- \frac{b_m}{2C_1^2}z_2^2\hat{\theta}\psi_2^T\psi_2 + \frac{b_m}{2C_1^2}z_2^2\theta\psi_2^T\psi_2 \\ &+ \frac{C_2^2}{2} + \frac{z_2^2}{2} + \frac{\bar{\varepsilon}_2^2}{2} + \frac{\bar{\lambda}_2^2}{2} + \frac{\bar{\lambda}_1^2}{4}\end{aligned} \tag{28}$$

Then, (28) can be rewritten as

$$\begin{aligned}\dot{V}_2 \leq& -a_1 b_m \eta_1^2 - a_2 b_m z_2^2 \\ &+ h_2 z_2 z_3 - \frac{\partial \alpha_1}{\partial \hat{\theta}}z_2\sum_{l=3}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ &+ \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 \\ &+ \frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l - \dot{\hat{\theta}}) + \Delta_1 + \Delta_2\end{aligned} \tag{29}$$

where

$$\Delta_2 = \frac{C_2^2}{2} + \frac{\bar{\varepsilon}_2^2}{2} + \frac{\bar{\lambda}_2^2}{2} + \frac{\bar{\lambda}_1^2}{4} \tag{30}$$

Step i ($i = 3, 4, \cdots, n-1$): Based on step 2, the iterative method can be used to obtain

$$\begin{aligned}\dot{V}_{i-1} \leq& -a_1 b_m \eta_1^2 - \sum_{k=2}^{i-1}a_k b_m z_k^2 + \sum_{k=1}^{i-1}\Delta_k \\ &+ h_{i-1}z_{i-1}z_i + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 \\ &+ \sum_{k=2}^{i-1}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k - \dot{\hat{\theta}}) \\ &- \sum_{k=1}^{i-2}\frac{\partial \alpha_k}{\partial \hat{\theta}}z_{k+1}\sum_{l=i}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l\end{aligned} \tag{31}$$

where

$$\Delta_i = \frac{C_i^2}{2} + \frac{\bar{\varepsilon}_i^2}{2} + \frac{\bar{\lambda}_i^2}{2} + \sum_{k=1}^{i-1}\sum_{l=1}^{k}\frac{\bar{\lambda}_l^2}{4} \tag{32}$$

we can take the Lyapunov function as follows

$$V_i = V_{i-1} + \frac{z_i^2}{2} \tag{33}$$

and then taking the time derivative of V_i yields

$$\begin{aligned}\dot{V}_i \leq & -a_1 b_m \eta_1^2 - \sum_{k=2}^{i-1} a_k b_m z_k^2 + \sum_{k=1}^{i-1} \Delta_k \\ & + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 + \sum_{k=2}^{i-1}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k \\ & - \dot{\hat{\theta}}) - \sum_{k=1}^{i-2}\frac{\partial\alpha_k}{\partial\hat{\theta}}z_{k+1}\sum_{l=i+1}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ & - \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}z_i\sum_{l=i+1}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ & + z_i[h_{i-1}z_{i-1} \\ & - \frac{\epsilon}{2C_i^2}z_i\psi_i^T\psi_i\sum_{k=1}^{i-2}\frac{\partial\alpha_k}{\partial\hat{\theta}}z_{k+1} + f_i \\ & + h_i x_{i+1} + \frac{z_i}{2} \\ & - \sum_{k=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_k}(f_k + h_k x_{k+1}) \\ & + z_i\sum_{k=1}^{i-1}(\frac{\partial\alpha_{i-1}}{\partial x_k})^2 - \sum_{k=0}^{i-1}\frac{\partial\alpha_{i-1}}{\partial\varrho_1^{(k)}}\varrho_1^{(k+1)} \\ & - \sum_{k=0}^{i-1}\frac{\partial\alpha_{i-1}}{\partial y_d^{(k)}}y_d^{(k+1)} \\ & - \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 \\ & - \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\sum_{k=2}^{i}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k \\ & + \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\delta\hat{\theta}] + \frac{\bar{\lambda}_i^2}{2} + \sum_{k=1}^{i-1}\frac{\bar{\lambda}_k^2}{4}\end{aligned} \tag{34}$$

Then, we can write

$$\begin{aligned}\dot{V}_i \leq & -a_1 b_m \eta_1^2 - \sum_{k=2}^{i-1} a_k b_m z_k^2 + \sum_{k=1}^{i-1} \Delta_k \\ & + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 \\ & + \sum_{k=2}^{i-1}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k - \dot{\hat{\theta}}) \\ & - \sum_{k=1}^{i-1}\frac{\partial\alpha_k}{\partial\hat{\theta}}z_{k+1}\sum_{l=i+1}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l \\ & + z_i(h_i x_{i+1} + F_i) + \frac{\bar{\lambda}_i^2}{2} + \sum_{k=1}^{i-1}\frac{\bar{\lambda}_k^2}{4}\end{aligned}$$

where

$$\begin{aligned}F_i = & h_{i-1}z_{i-1} - \frac{\epsilon}{2C_i^2}z_i\psi_i^T\psi_i\sum_{k=1}^{i-2}\frac{\partial\alpha_k}{\partial\hat{\theta}}z_{k+1} + f_i \\ & - \sum_{k=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_k}(f_k + h_k x_{k+1}) \\ & + z_i\sum_{k=0}^{i-1}(\frac{\partial\alpha_{i-1}}{\partial x_k})^2 - \sum_{k=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial\varrho_1^{(k)}}\varrho_1^{(k+1)} \\ & - \sum_{k=0}^{i-1}\frac{\partial\alpha_{i-1}}{\partial y_d^{(k)}}y_d^{(k+1)} - \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 \\ & - \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\sum_{k=2}^{i}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k + \frac{\partial\alpha_{i-1}}{\partial\hat{\theta}}\delta\hat{\theta}\end{aligned}$$

Similarly, according to (22) and (32), it produces

$$\begin{aligned}\dot{V}_i \leq & -a_1 b_m \eta_1^2 - \sum_{k=2}^{i} a_k b_m z_k^2 + \sum_{k=1}^{i} \Delta_k + z_i z_{i+1} \\ & + \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2\psi_1^T\psi_1 + \sum_{k=2}^{i}\frac{\epsilon}{2C_k^2}z_k^2\psi_k^T\psi_k - \dot{\hat{\theta}}) \\ & - \sum_{k=1}^{i-1}\frac{\partial\alpha_k}{\partial\hat{\theta}}z_{k+1}\sum_{l=i+1}^{n}\frac{\epsilon}{2C_l^2}z_l^2\psi_l^T\psi_l\end{aligned} \tag{35}$$

Remark 4: This paper only designs one adaptive law $\dot{\hat{\theta}}$ in each step of virtual control input, which is similar to literature [31]. This greatly reduces computational complexity. Because of the term $(\partial\alpha_{i-1}/\partial\hat{\theta})\dot{\hat{\theta}}$ contains the terms $z_{i+1}, \cdots, z_n$, the fuzzy logic system ${W_i}^T\psi_i(Z_i)$ can not be directly used to approximate it. To overcome this difficulty, we divided the therm $(\partial\alpha_{i-1}/\partial\hat{\theta})\dot{\hat{\theta}}$ into two parts in (34): $(\partial\alpha_{i-1}/\partial\hat{\theta})[(\epsilon/2C_1^2)\eta_1^2\psi_1^T\psi_1 + \sum_{k=2}^{i}(\epsilon/2C_k^2)z_k^2\psi_k^T\psi_k - \delta\hat{\theta}]$ and $(\partial\alpha_{i-1}/\partial\hat{\theta})$ $[\sum_{k=i+1}^{n}(\epsilon/2C_k^2)z_k^2\psi_k^T\psi_k]$. The first term can be summed up in the package function F_i, and the second part will be dealt with in the later design steps.

Step n: The event triggering mechanism is used to design the actual controller $v(t)$ in step n. Now, select the Lyapunov function candidate V_n as

$$V_n = V_{n-1} + \frac{z_n^2}{2} \tag{36}$$

The derivative of V_n can be obtained

$$\begin{aligned}\dot{V}_n &\leq -a_1 b_m \eta_1^2 - \sum_{k=2}^{n-1} a_k b_m z_k^2 + \sum_{k=1}^{n-1} \Delta_k \\ &+ \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2 \psi_1^T \psi_1 \\ &+ \sum_{k=2}^{n-1} \frac{\epsilon}{2C_k^2} z_k^2 \psi_k^T \psi_k - \dot{\hat{\theta}}) \\ &+ z_n[h_{n-1} z_{n-1} \\ &- \frac{\epsilon}{2C_n^2} z_n \psi_n^T \psi_n \sum_{k=1}^{n-1} \frac{\partial \alpha_k}{\partial \hat{\theta}} z_{k+1} + f_n \\ &+ h_n G_\sigma v + h_n g + \frac{z_n}{2} \\ &- \sum_{k=1}^{n-1} \frac{\partial \alpha_{n-1}}{\partial x_k}(f_k + x_{k+1}) \\ &+ z_n \sum_{k=1}^{n-1} (\frac{\partial \alpha_{n-1}}{\partial x_k})^2 - \sum_{k=0}^{n-1} \frac{\partial \alpha_{i-1}}{\partial \varrho_1^{(k)}} \varrho_1^{(k+1)} \\ &- \sum_{k=0}^{n-1} \frac{\partial \alpha_{n-1}}{\partial y_d^{(k)}} y_d^{(k+1)} - \frac{\partial \alpha_{n-1}}{\partial \hat{\theta}} \delta \hat{\theta}] \\ &+ \frac{\bar{\lambda}_n^2}{2} + \sum_{k=1}^{n-1} \frac{\bar{\lambda}_k^2}{4}\end{aligned} \tag{37}$$

Therefore, we can rewrite (37) as

$$\begin{aligned}\dot{V}_n &\leq -a_1 b_m \eta_1^2 - \sum_{k=2}^{n-1} a_k b_m z_k^2 + \sum_{k=1}^{n-1} \Delta_k \\ &+ \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2 \psi_1^T \psi_1 \\ &+ \sum_{k=2}^{n-1} \frac{\epsilon}{2C_k^2} z_k^2 \psi_k^T \psi_k - \dot{\hat{\theta}}) \\ &+ z_n(h_n G_\sigma v + h_n g + F_n) \\ &+ \frac{\bar{\lambda}_n^2}{2} + \sum_{k=1}^{n-1} \frac{\bar{\lambda}_k^2}{4}\end{aligned} \tag{38}$$

where

$$\begin{aligned}F_n &= h_{n-1} z_{n-1} - \frac{\epsilon}{2C_n^2} z_n^2 \psi_n^T \psi_n \sum_{k=1}^{n-1} \frac{\partial \alpha_k}{\partial \hat{\theta}} z_{k+1} \\ &+ f_n + \frac{z_n}{2} - \sum_{k=1}^{n-1} \frac{\partial \alpha_{n-1}}{\partial x_k}(f_k + h_k x_{k+1}) \\ &+ z_n \sum_{k=1}^{n-1} (\frac{\partial \alpha_{n-1}}{\partial x_k})^2 - \sum_{k=0}^{n-1} \frac{\partial \alpha_{n-1}}{\partial \varrho_1^{(k)}} \varrho_1^{(k+1)} \\ &- \sum_{k=0}^{n-1} \frac{\partial \alpha_{n-1}}{\partial y_d^{(k)}} y_d^{(k+1)} - \frac{\partial \alpha_{n-1}}{\partial \hat{\theta}} \delta \hat{\theta}\end{aligned}$$

Next, the adaptive controller is given as

$$\omega(t) = \alpha_n - \bar{\mu} \tanh\left(\frac{z_n \bar{\mu}}{\gamma}\right) \tag{39}$$

The triggering event is defined as

$$\begin{aligned}v(t) &= \omega(t_s), \quad \forall t \in [t_s, t_{s+1}), \quad p \in \mathbb{Z}^+ \\ t_{s+1} &= \inf\left\{t \in \mathbb{R}^+ \,||e_v(t)| \geq \mu\right\}\end{aligned} \tag{40}$$

where μ, γ and $\bar{\mu} > \mu$ are all ensure positive constant, and the measurement error is given as

$$e_v(t) = \omega(t) - v(t) \tag{41}$$

Similar to the analysis of [24], the inequality $|\omega(t) - v(t)| \leq \mu$ holds for the time $t \in [t_s, t_{s+1})$, so there exists a continuous function $\chi(t)$, which satisfies $|\chi(t)| \leq 1$ with $\chi(t_s) = 0$ and $\chi(t_{s+1}) = \pm 1$, the following expression holds

$$v(t) = \omega(t) - \chi(t)\mu \tag{42}$$

Remark 5: μ is the fixed threshold. The value of μ needs to make the system stable and has the least number of events triggered at the same time

By taking (6), (11), (39) and $v(t) = \omega(t) - \chi(t)\mu$ into consideration, one has

$$\begin{aligned}\dot{V}_n &\leq -a_1 b_m \eta_1^2 - \sum_{k=2}^{n-1} a_k b_m z_k^2 + \sum_{k=1}^{n} \Delta_k \\ &+ \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2 \psi_1^T \psi_1 + \sum_{k=2}^{n-1} \frac{\epsilon}{2C_k^2} z_k^2 \psi_k^T \psi_k \\ &- \dot{\hat{\theta}}) + z_n h_n G_\sigma \alpha_n + z_n h_n g + \frac{b_m}{2C_n^2} z_n^2 \theta \psi_n^T \psi_n \\ &+ z_n h_n G_\sigma \left(-\bar{\mu} \tanh\left(\frac{z_n \bar{\mu}}{\gamma}\right) - \chi(t)\mu\right)\end{aligned} \tag{43}$$

Note that the hyperbolic tangent function $\tanh(\cdot)$ has the following property [35]:

$$0 \leq |\iota| - \iota \tanh\left(\frac{\iota}{\gamma}\right) \leq 0.2785\gamma \tag{44}$$

where $\gamma > 0$ and $\iota \in \mathbb{R}$, eventually we can get

$$\begin{aligned}\dot{V}_n &\leq -a_1 b_m \eta_1^2 - \sum_{k=2}^{n-1} a_k b_m z_k^2 + \sum_{k=1}^{n} \Delta_k \\ &+ \frac{b_m}{\epsilon}\tilde{\theta}(\frac{\epsilon}{2C_1^2}\eta_1^2 \psi_1^T \psi_1 \\ &+ \sum_{k=2}^{n-1} \frac{\epsilon}{2C_k^2} z_k^2 \psi_k^T \psi_k - \dot{\hat{\theta}}) \\ &+ z_n h_n G_\sigma \alpha_n + z_n h_n g \\ &+ \frac{b_m}{2C_n^2} z_n^2 \theta \psi_n^T \psi_n + 0.2785\gamma h_n G_\sigma\end{aligned} \tag{45}$$

By using the virtual control law α_n and Lemma 3, it is easy to obtain the following inequalities

$$z_n h_n G_\sigma \alpha_n \le -a_n b_m {z_n}^2 - \frac{h_n G_\sigma z_n^2}{2d^2} - \frac{b_m}{2C_n^2} z_n^2 \hat{\theta}\psi_n^T \psi_n \quad (46)$$

$$z_n h_n g \le \frac{h_n G_\sigma z_n^2}{2d^2} + \frac{b_M d^2 \bar{g}^2}{2b_m} \quad (47)$$

where $d > 0$ is a design parameter. Combing (45) with (47) and (46), together with the fact $\tilde{\theta}\hat{\theta} \le (-1/2)\tilde{\theta}^2 + (1/2)\theta^2$ result in

$$\dot{V}_n \le -a_1 b_m \eta_1^2 - \sum_{k=2}^{n} a_k b_m z_k^2 - \frac{b_m \delta}{2\epsilon}\tilde{\theta}^2 + \rho_0 \quad (48)$$

where $\rho_0 = (b_m\delta/2\epsilon)\theta^2 + \sum_{k=1}^{n}\Delta_k + 0.2785\gamma d_M + b_M/d^2\bar{g}^2 2b_m$. Defining $\gamma_0 = \min\{2b_m a_i, \delta, i = 1, 2, \cdots, n\}$, (48) can be rewritten as

$$\dot{V}_n \le \gamma_0 V + \rho_0 \quad (49)$$

Theorem 1: Consider the uncertain nonlinear systems (1), the adaptive law (16) and the event-trigger mechanism (40) controller. If the assumptions 1-3 are satisfied, then the inter-execution intervals $\{t_{s+1} - t_s\}$ for $\forall s \in Z^+$ are lower bounded by a positive constant $t^* > 0$ such that Zeno-behavior does not occur.

Proof 1: In order to prove that there exists a constant $t^* > 0$ such that $\{t_{s+1} - t_s\} \ge t^*, \forall s \in Z^+$, by recalling $e_v(t) = \omega(t) - v(t), \forall t \in (t_s, t_{s+1})$, we obtain

$$\frac{d}{dt}|e_v| = \frac{d}{dt}(e_v * e_v)^{\frac{1}{2}} = sign(e_v)\dot{e}_v \le |\dot{\omega}| \quad (50)$$

It can be seen from (39) that $\dot{\omega}(t)$ is a function of the variables, $x, \hat{\theta}$ and $\psi(Z_n)$, where x and $\hat{\theta}$ have been proved to be bounded, and $\psi(Z_n)$ is a differentiable Gauss function, so $\dot{\omega}(t)$ must be a continuous function. Hence, there must exist a constant $\bar{\omega} > 0$ such that $|\dot{\omega}(t)| < \bar{\omega}$. From $e_v(t_s) = 0$ and $\lim_{t \to t_{s+1}} e_v(t) = \mu$, we obtain that the lower bound of inter-execution interval t^* must satisfy $t^* \ge m/s$, the Zeno-behavior [36] is successfully avoided.

The proof of the Theorem is therefore completed.

Remark 6: Based on the above proof, the designed adaptive controller (14)-(15) with parameter update law (17) and trigger mechanism (39), (40) not only ensures that the tracking error does not violate the preset performance function, but also ensures that all signals of the closed-loop system are bounded, and also realizes the event trigger mechanism well.

IV. Simulation

In this section, the effectiveness of the proposed control method is verified by the following numerical simulation example.

A second-order nonlinear system with unknown control direction is considered as follows:

$$\begin{cases} \dot{x}_1 = x_2 + \lambda_1, \\ \dot{x}_2 = A\cos(x_1) + Bu + \lambda_2, \\ y \;= x_1 \end{cases} \quad (51)$$

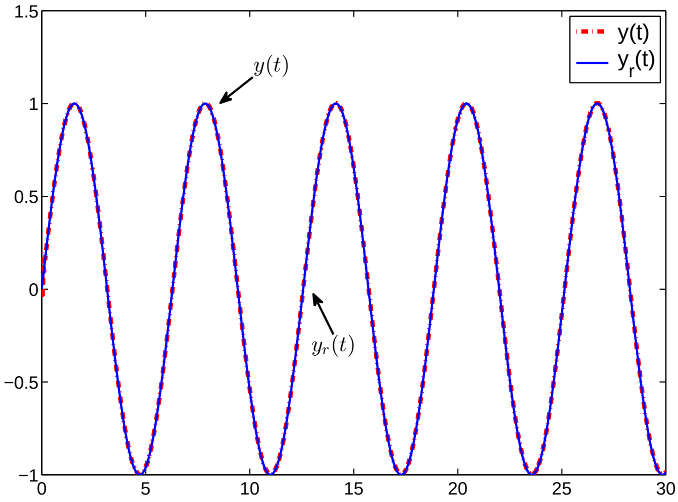

Fig. 1. Desired signal $y_r(t)$ and system output $y(t)$.

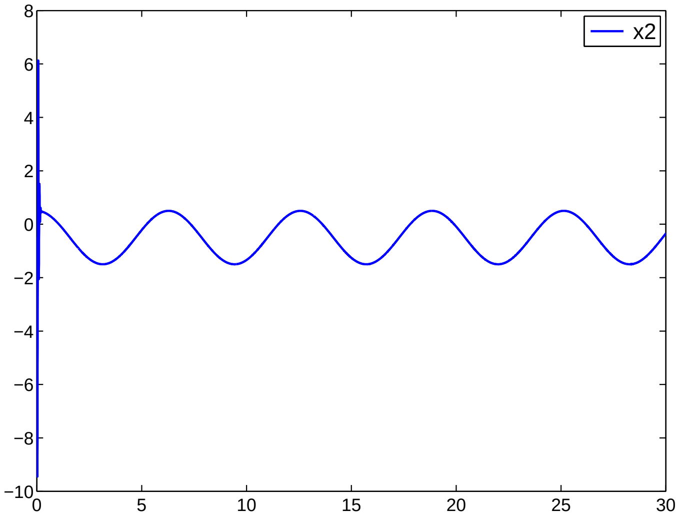

Fig. 2. System state x_2.

where x_1 and x_2 are the state variables, y is the system output, λ_1 and λ_2 are the disturbance, and u is the actual control input, which defined in (2). And the nonsymmetrical input saturation limits are chosen as $u_{max} = 500$ and $u_{min} = -400$, respectively.

To verify the tracking performance of the proposed algorithm, the reference signal is chosen as $y_r = \sin(t)$. The parameters of the prescribed performance function ϱ_1 is specified as $\varrho_0 = 1$, $\varrho_\infty = 0.04$ and $\ell = 0.4$. The control parameters are selected as $A = 9$, $B = 0.9$, $C_1 = 50$, $C_2 = 50$, $a_1 = 100$, $a_2 = 70$, $d = 1$, $\epsilon = 1$, $\delta = 1$, $\gamma = 10$, $\mu = 0.1$, $\bar{\mu} = 7$.The disturbances are taken as $\lambda_1 = 0.5$, $\lambda_2 = 0.8$. The initial conditions are taken as $[x_1(0), x_2(0)]^T = [0.2 - 0.5]^T$ and $\hat{\theta}(0) = 0$. The simulation results are shown by Figs. 1-8. Desired signal $y_r(t)$ and system output $y(t)$ are shown in Fig. 1. Fig. 2 displays the system state x_2. The tracking error of the proposed method is presented in Fig. 3. The bounded curve of adaptive rate $\hat{\theta}$ is shown in Fig. 4. The trajectories of event-triggered control signal $v(t)$ and continuous control signal $\omega(t)$ are shown in Fig. 5. Figs. 6 and 7 show the event-triggered control input $v(t)$ and the saturated control input $u(t)$, respectively. The time intervals of each event are shown in Fig. 8.

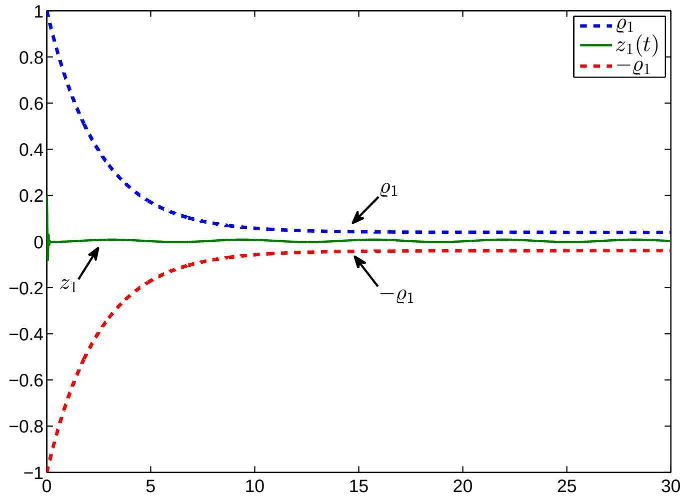

Fig. 3. Tracking error z_1 under the prescribed performance constraint ϱ_1.

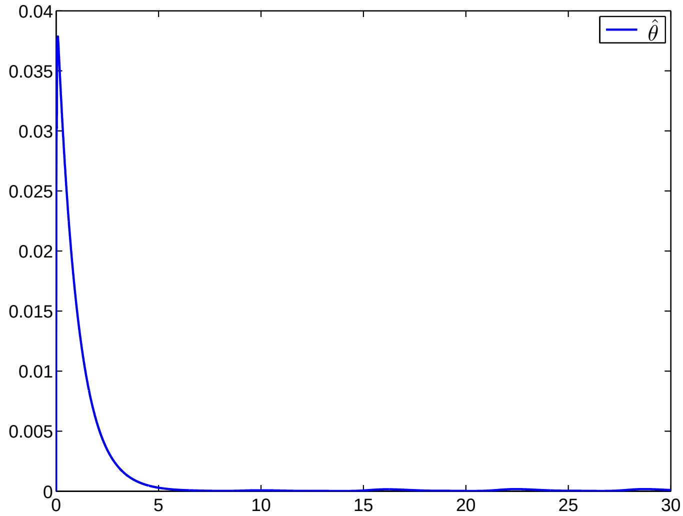

Fig. 4. Adaptive law $\hat{\theta}$.

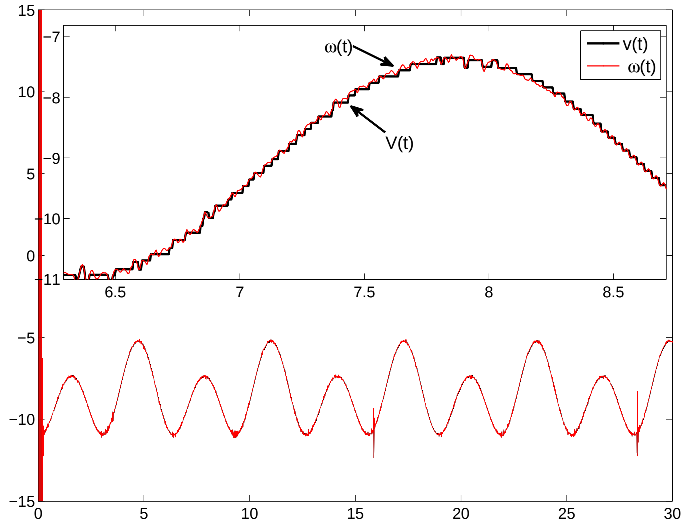

Fig. 5. The trajectories of event-triggered control signal $v(t)$ and continuous control signal $\omega(t)$.

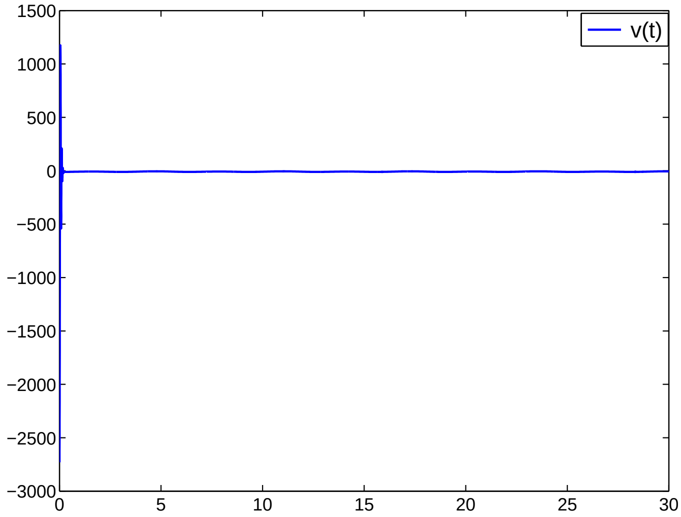

Fig. 6. Event-triggered control signal $v(t)$.

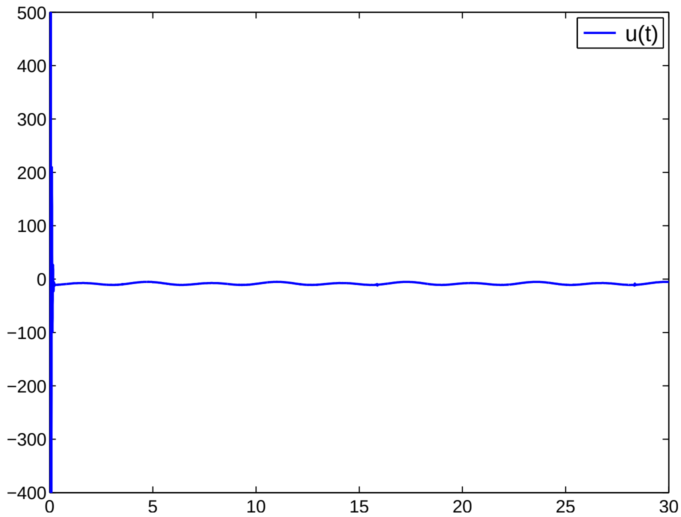

Fig. 7. Actual control signals $u(t)$ with saturation constraints.

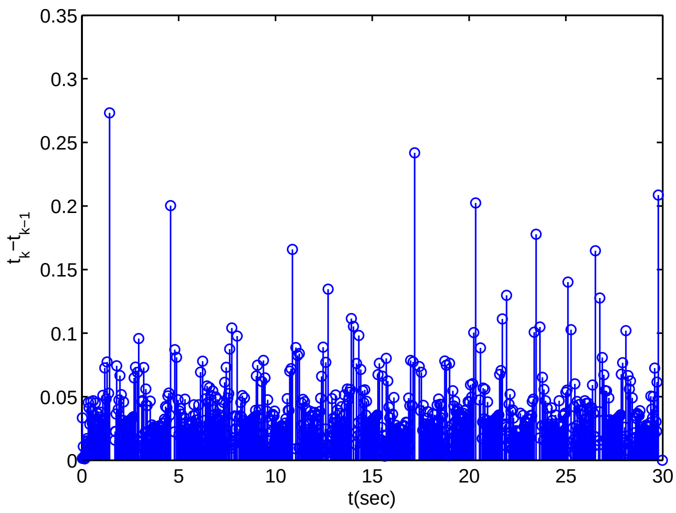

Fig. 8. Time interval of triggering events.

V. Conclusion

In this paper, a new control scheme based on event triggering is designed for strictly feedback uncertain nonlinear systems with input saturation constraints. The unknown function is approximated by adaptive fuzzy control, a new error exchange function is proposed, and the tracking error is constrained by the preset constraint function. An event-triggered fixed threshold strategy is designed, which is theoretically and experimentally proved to be feasible and effective. How to extend the algorithm to nonaffine stochastic nonlinear control system and other event triggering strategies will be a further topic.

REFERENCES

[1] M. Chen, X. Liu, and H. Wang, "Adaptive robust fault-tolerant control for nonlinear systems with prescribed performance," *Nonlinear Dynamics*, vol. 81, no. 4, pp. 1727–1739, 2015.

[2] H. Chen, C. Wang, B. Zhang, and D. Zhang, "Saturated tracking control for nonholonomic mobile robots with dynamic feedback," *Transactions of the Institute of Measurement and Control*, vol. 35, no. 2, pp. 105–116, 2013.

[3] M. M. Polycarpou, "Stable adaptive neural control scheme for nonlinear systems," *IEEE Transactions on Automatic Control*, vol. 41, no. 3, pp. 447–451, 1996.

[4] T. Zhang, S. S. Ge, and C. C. Hang, "Stable adaptive control for a class of nonlinear systems using a modified lyapunov function," *IEEE Transactions on Automatic Control*, vol. 45, no. 1, pp. 129–132, 2000.

[5] Y.-J. Liu, S. Tong, and Y. Li, "Adaptive neural network tracking control for a class of non-linear systems," *International Journal of Systems Science*, vol. 41, no. 2, pp. 143–158, 2010.

[6] A. J. Koshkouei, A. S. Zinober, and K. J. Burnham, "Adaptive sliding mode backstepping control of nonlinear systems with unmatched uncertainty," *Asian Journal of Control*, vol. 6, no. 4, pp. 447–453, 2004.

[7] Q. Shen, P. Shi, T. Zhang, and C.-C. Lim, "Novel neural control for a class of uncertain pure-feedback systems," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 4, pp. 718–727, 2014.

[8] Y.-X. Li and G.-H. Yang, "Adaptive neural control of pure-feedback nonlinear systems with event-triggered communications," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 12, pp. 6242–6251, 2018.

[9] C. P. Chen, Y.-J. Liu, and G.-X. Wen, "Fuzzy neural network-based adaptive control for a class of uncertain nonlinear stochastic systems," *IEEE Transactions on Cybernetics*, vol. 44, no. 5, pp. 583–593, 2014.

[10] C. F. Hsu, "Chattering-free adaptive wavelet neural network controller design for a class of nonlinear systems," *Engineering Letters*, vol. 17, no. 3, pp. 165-172, 2009.

[11] J. Dong and G. Yang, "Reliable state feedback control of t-s fuzzy systems with sensor faults," *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 2, pp. 421–433, 2015.

[12] H. Wang, W. Liu, J. Qiu, and P.-X. Liu, "Adaptive fuzzy decentralized control for a class of strong interconnected nonlinear systems with unmodeled dynamics," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 2, pp. 836–846, 2018.

[13] H. Wang, W. Liu, P.-X. Liu, and H.-K. Lam, "Adaptive fuzzy decentralized control for a class of interconnected nonlinear system with unmodeled dynamics and dead zones," *Neurocomputing*, vol. 214, pp. 972–980, 2016.

[14] Henry N., Afiq A. Dahlan, Affandi M. Nasib, Azhar A. Aziz, and Sumeru, "Indoor temperature control and energy saving potential of split unit air conditioning system using fuzzy logic controller," *International Journal of Computer Science*, vol. 43, no. 4, pp. 402-405, 2016.

[15] S. A. Malek, M. Shahrokhi, E. Vafa, and A. Moradvandi, "Adaptive prescribed performance control of switched mimo uncertain nonlinear systems subject to unmodeled dynamics and input nonlinearities," *International Journal of Robust and Nonlinear Control*, vol. 28, no. 18, pp. 5981–5996, 2018.

[16] X. Liu, H. Wang, C. Gao, and M. Chen, "Adaptive fuzzy funnel control for a class of strict feedback nonlinear systems," *Neurocomputing*, vol. 241, pp. 71–80, 2017.

[17] J.-X. Zhang and G.-H. Yang, "Adaptive prescribed performance control of nonlinear output-feedback systems with unknown control direction," *International Journal of Robust and Nonlinear Control*, vol. 28, no. 16, pp. 4696–4712, 2018.

[18] M. Hou and Y. Wang, "Data-driven adaptive terminal sliding mode control with prescribed performance," *Asian Journal of Control*, vol. 23, no. 2, pp. 774–785, 2021.

[19] W. Heemels, K. H. Johansson, and P. Tabuada, "An introduction to event-triggered and self-triggered control," *2012 IEEE 51st IEEE Conference on Decision and Control (CDC)*, pp. 3270–3285, 2012.

[20] A. Adaldo, F. Alderisio, D. Liuzza, G. Shi, D. V. Dimarogonas, M. Di Bernardo, and K. H. Johansson, "Event-triggered pinning control of complex networks with switching topologies," *53rd IEEE Conference on Decision and Control*, pp. 2783–2788, 2014.

[21] P. Tallapragada and N. Chopra, "Decentralized event-triggering for control of nonlinear systems," *IEEE Transactions on Automatic Control*, vol. 59, no. 12, pp. 3312–3324, 2014.

[22] Y. Li and G. Yang, "Model-based adaptive event-triggered control of strict-feedback nonlinear systems," *IEEE Transactions on Neural Networks*, vol. 29, no. 4, pp. 1033–1045, 2018.

[23] W. Xu, D. W. C. Ho, L. Li, and J. Cao, "Event-triggered schemes on leader-following consensus of general linear multiagent systems under different topologies," *IEEE Transactions on Cybernetics*, vol. 47, no. 1, pp. 212–223, 2017.

[24] L. Xing, C. Wen, Z. Liu, H. Su, and J. Cai, "Event-triggered adaptive control for a class of uncertain nonlinear systems," *IEEE Transactions on Automatic Control*, vol. 62, no. 4, pp. 2071–2076, 2017.

[25] Q. Fan and G. Yang, "Event-based fuzzy adaptive fault-tolerant control for a class of nonlinear systems," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 5, pp. 2686–2698, 2018.

[26] L. Xing, C. Wen, Z. Liu, H. Su, and J. Cai, "Adaptive compensation for actuator failures with event-triggered input," *Automatica*, vol. 85, pp. 129–136, 2017.

[27] Y. Yang and D. Yue, "Nns-based event-triggered consensus control of a class of uncertain nonlinear multi-agent systems,"*Asian Journal of Control*, vol. 21, no. 2, pp. 660–673, 2019.

[28] X. Jin, J. Qin, Y. Shi, and W.-X. Zheng, "Auxiliary fault tolerant control with actuator amplitude saturation and limited rate," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 10, pp. 1816–1825, 2018.

[29] H. Wang, B. Chen, X. Liu, K. Liu, and C. Lin, "Robust adaptive fuzzy tracking control for pure-feedback stochastic nonlinear systems with input constraints," *IEEE Transactions on Cybernetics*, vol. 43, no. 6, pp. 2093–2104, 2013.

[30] Y. Li and Z. Lin, "Saturation-based switching anti-windup design for linear systems with nested input saturation," *Automatica*, vol. 50, no. 11, pp. 2888–2896, 2014.

[31] H. Wang, B. Chen, X. Liu, K. Liu, and C. Lin, "Robust adaptive fuzzy tracking control for pure-feedback stochastic nonlinear systems with input constraints," *IEEE Transactions on Cybernetics*, vol. 43, no. 6, pp. 2093–2104, 2013.

[32] C. Wen, J. Zhou, Z. Liu, and H. Su, "Robust adaptive control of uncertain nonlinear systems in the presence of input saturation and external disturbance," *IEEE Transactions on Automatic Control*, vol. 56, no. 7, pp. 1672–1678, 2011.

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

[34] H. Deng and M. Krstić, "Stochastic nonlinear stabilizationi: a backstepping design," *Systems & Control Letters*, vol. 32, no. 3, pp. 143–150, 1997.

[35] B. Ren, P. P. San, S. S. Ge, and T. H. Lee, "Adaptive dynamic surface control for a class of strict-feedback nonlinear systems with unknown backlash-like hysteresis," *2009 American Control Conference*, pp. 4482–4487, 2009.

[36] K. H. Johansson, M. Egerstedt, J. Lygeros, and S. Sastry, "On the regularization of zeno hybrid automata," *Systems & Control Letters*, vol. 38, no. 3, pp. 141–150, 1999.