Adaptive Asymptotic Tracking Control of Uncertain Nonlinear Systems Based on Taylor Decoupling and Event-Trigger

Li-Bing Wu, Ju H. Park, *Senior Member, IEEE*, Xiang-Peng Xie, *Member, IEEE*, and Ya-Feng Li

***Abstract*—This article studies the robust adaptive asymptotic tracking control problem for uncertain nonlinear systems with event-triggered inputs. Contrary to the existing results, a novel nonaffine nonlinear control input separated design scheme is developed based on the Taylor decoupling technique instead of the previous approximation ways. Correspondingly, the augmented dimension parameter updated laws and the unknown bound estimation of the compounded disturbance with a positive continuous integrable function are skillfully introduced. Also, by introducing a suitable decreasing function of tracking error variables, an improved adaptive event-triggered mechanism is constructed to achieve the asymptotic tracking and the communication load can be effectively alleviated. Moreover, it is shown that all the signals in the closed-loop system are uniformly bounded and the tracking errors converge to zero in a preset compact set. Finally, the validity of the proposed method is illustrated by simulation on an inverted pendulum model.**

***Index Terms*—Adaptive control, asymptotic tracking, event-triggered control (ETC), Taylor decoupling, uncertain nonlinear system.**

I. Introduction

As IS well known, the vast majority of practical engineering systems can be modeled by the various forms of linear or nonlinear dynamic differential equations [1]–[5]. More especially, an adaptive backstepping method, that is, a quite effective control technique, has applied to several different types of nonlinear plants [6]–[10]. In [11], the robust adaptive global tracking control of strict-feedback nonlinear systems with parameter uncertainties, external disturbances, and input saturations was developed by introducing a smooth approximation function and a Nussbaum function, respectively. Based on the direct adaptive method and backstepping process, the asymptotic tracking [12] was achieved for uncertain nonlinear systems subject to actuator dead-zone and hysteresis nonlinearities. Recently, a fault-tolerant control (FTC) based on performance technique [13] was presented for nonlinear systems with actuator failures and unknown control directions. For stochastic nonlinear time-delayed systems subject to actuator saturations, an output-feedback control scheme was developed in [14] via constructing the corresponding auxiliary system. It is noted that substantial research results are all devoted to the strict-feedback nonlinear systems rather than the nonaffine nonlinear systems. The intelligent approximation ways, such as fuzzy logic systems (FLSs) [15]–[19] or neural networks (NNs) [20]–[23], have been widely used for controller decoupling by implicit function theorem or mean-value theorem.

Unfortunately, we know that the intelligent approximation abilities are effective only in a proper compact set, which cannot be preset and thus the obtained analysis results are relatively conservative. Meanwhile, in order to reduce the amount of sample-data and communication, the ETC methods have been widely studied and gradually replaced the traditional periodical sampled-data scheme. Therefore, many significant event-triggered strategies [24]–[33] have been obtained. The designed event-driven communication scheme [34] can effectively use the network resources for the networked switched systems. In [35], an adaptive event-triggering FTC is addressed via the generalized fuzzy hyperbolic approximation technique. The novel adaptive event-triggered tracking control method [36] and the event-triggered FTC design scheme [37] were successfully applied for uncertain nonlinear systems, respectively. In [38], the adaptive event-triggered fault-tolerant controller was designed for uncertain nonlinear nonstrict-feedback systems by constructing fuzzy observer. Unfortunately, the above methods are limited to the asymptotic tracking control and the design of event-triggered mechanism for uncertain nonaffine nonlinear systems with unknown parameter vectors. Thus, it is more challenging to develop a novel adaptive event-triggering strategy to solve the addressed stability problem.

Motivated by the corresponding discussions, a novel adaptive asymptotic tracking-based event-trigger control design of

Manuscript received February 13, 2020; revised July 16, 2020; accepted October 24, 2020. Date of publication December 9, 2020; date of current version March 17, 2022. This work was supported in part by the National Research Foundation of Korea grant funded by the Korea Government (Ministry of Science and ICT) under Grant 2019R1A5A8080290, in part by the National Natural Science Foundation of China under Grant 62022044, and in part by the Jiangsu Natural Science Foundation for Distinguished Young Scholars under Grant BK20190039. This article was recommended by Associate Editor S. Song. *(Corresponding author: Ju H. Park.)*

Li-Bing Wu is with the School of Science, University of Science and Technology Liaoning, Anshan 114051, China, and also with the Department of Electrical Engineering, Yeungnam University, Kyongsan 38541, South Korea (e-mail: beyondwlb@163.com).

Ju H. Park is with the Department of Electrical Engineering, Yeungnam University, Kyongsan 38541, South Korea (e-mail: jessie@ynu.ac.kr).

Xiang-Peng Xie is with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China (e-mail: xiexiangpeng1953@163.com).

Ya-Feng Li is with the Institute of Electrical Engineering, Yanshan University, Qinhuangdao 066004, China (e-mail: y.l.li@foxmail.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TSMC.2020.3034579.

Digital Object Identifier 10.1109/TSMC.2020.3034579

uncertain nonaffine nonlinear systems is proposed in this article. Concretely, the major contributions and novelties of the work are marked as follows.

1) Without using any approximation technique as in [7], [15]–[23], and [35], the adaptive asymptotic tracking control is first extended to uncertain nonaffine nonlinear systems subject to unknown parameter vectors and event-triggered inputs.
2) Different from the existing results [8], [11], and [13] whose tracking errors can only be uniformly ultimately bounded (UUB), the augmented dimension parameter updated laws and the unknown bound estimation of the compounded disturbance with a positive continuous integrable function are effectively constructed. Accordingly, a novel nonaffine nonlinear decoupling strategy based on the Taylor theorem is given to achieve the desired asymptotic tracking control objective.
3) Not only the considered nonlinear systems of this article can be reviewed as an extension of [36], where the considered ones are strict-feedback form. But also compared with [36], an improved adaptive ETC strategy with a suitable decreasing function including tracking error variables is proposed here. The computation load of the communication process is thus substantially alleviated.

II. Problem Formulation

Consider a class of nonaffine nonlinear systems as follows:

$$\begin{aligned} \dot{x}_k &= g_k(X_k)x_{k+1} + f_k(X_k) + \psi_k^T(X_k)\eta_k \\ k &= 1, 2, \ldots, n-1 \\ \dot{x}_n &= f_n(X, u) + \psi_n^T(X)\eta_n + d(t) \\ y &= x_1 \end{aligned} \tag{1}$$

where $X = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^n, X_k = [x_1, x_2, \ldots, x_k]^T \in \mathbb{R}^k, k = 1, 2, \ldots, n-1, u \in \mathbb{R}, y \in \mathbb{R}$ and $d \in \mathbb{R}$ are the system state vectors, the actual input, the control output, and the additive disturbance, respectively; $\eta_k \in \mathbb{R}^p$ denotes the unknown parameter vector; the nonlinear functions $f_k(\cdot), g_k(\cdot) : \mathbb{R}^k \to \mathbb{R}, \psi_i(\cdot) : \mathbb{R}^i \to \mathbb{R}^p, i = 1, 2, \ldots, n$ and $f_n(\cdot) : \mathbb{R}^{n+1} \to \mathbb{R}$, respectively, represent the known and unknown smooth functions with $f_k(\mathbf{0}) = 0, \psi_i(\mathbf{0}) = \mathbf{0}, g_k(X_k) \neq 0, k = 1, 2, \ldots, n-1$, and $f_n(\mathbf{0}, 0) = 0$.

Our control objectives are that: 1) all signals in the closed-loop signals are bounded within a given compact set; 2) the system output tracking error $e_1 = y - y_r$ asymptotically converges to zero; and 3) the communication load is effectively reduced. To achieve this goal, we make the following necessary assumptions and useful lemmas.

Assumption 1: Both the reference signal y_r, its kth order derivatives $y_r^{(k)}, k = 1, 2, \ldots, n$, and the additive disturbance d are continuous and bounded, which implies that $|y_r| \leq y_r^*, |y_r^{(k)}| \leq y_{rk}^*$ and $|d| \leq d^*$ with y_r^*, y_{rk}^*, and d^* being the unknown upper bounds, respectively.

Assumption 2: For a given compact set $\Omega_X \in \mathbb{R}^n$, there exist two positive constants f_l^* and f_u^* such that

$$0 < f_l^* \leq \frac{\partial f_n(X, 0)}{\partial u} \leq f_u^* \tag{2}$$

for all $X \in \Omega_X$.

Remark 1: In practice, a large number of dynamical plants including underwater robots, electrical and mechanical systems, and chemical processes can be modeled as the nonaffine nonlinear structure. Meanwhile, it is readily seen that the considered nonlinear system in [36] is a special case of (1).

Remark 2: Clearly, it follows from Assumption 1 that the reference trajectory y_r and its derivatives $y_r^{(k)}, k = 1, 2, \ldots, n$ are continuous and bounded. It should be pointed out that (2) of Assumption 2 is looser than the following condition satisfying:

$$0 < f_l^* \leq \frac{\partial f_n(X, u)}{\partial u} \leq f_u^* \quad \forall X \in \mathbb{R}^n, u \in \mathbb{R} \tag{3}$$

as in [15] and [20]. For example, consider the nonaffine nonlinear function $f_n(X, u) = u + 0.5\sin(uX)$ and then it is easy to verify that $(\partial f_n(X, u)/\partial u) = 1 + 0.5X\cos(uX)$ does not satisfy (3). However, we can infer that $0.8 \leq (\partial f_n(X, 0)/\partial u) \leq 1.2$ on a given compact set $[-0.4, 0.4]$ and therefore that (2) holds. By (2), the actual input u of nonlinear coupling term $f_n(X, u)$ is effectively separated via the following Taylor expansion technique.

Lemma 1: Let Ω_X be a given compact set of $\mathbb{R}^n$, then the nonlinear coupling function $f_n(X, u)$ of (1) can be decoupled as the following affine form:

$$\begin{aligned} \dot{x}_k &= g_k(X_k)x_{k+1} + f_k(X_k) + \psi_k^T(X_k)\eta_k \\ k &= 1, 2, \ldots, n-1 \\ \dot{x}_n &= g_n(X, 0)u + C(X) + \psi_n^T(X)\eta_n + d(t) \\ y &= x_1 \end{aligned} \tag{4}$$

where $C(X) = f_n(X, 0) + h_n(X, u)$ with $h_n(X, u) = [(\partial g_n(X, 0))/\partial u]u^2 + (1/2!)[(\partial^2 g_n(X, 0))/\partial u^2]u^3 + \cdots + (1/n!)[(\partial^n g_n(X, 0))/\partial u^n]u^{n+1} + R_{n+1}(X, u)u$ and $g_n(X, u) = (\partial f(X, u)/\partial u)\mid_{u=u_\lambda}$ with $u_\lambda = \lambda u, \lambda \in (0, 1)$.

Proof: Using Assumption 2 and the mean value theorem, the nonaffine nonlinear function $f_n(X, u)$ of (1) can be separated into

$$f_n(X, u) = f_n(X, 0) + g_n(X, u)u \tag{5}$$

where $g_n(X, u) = (\partial f(X, u)/\partial u)\mid_{u=u_\lambda}$ with $u_\lambda = \lambda u, \lambda \in (0, 1)$.

Clearly, it can be seen that $g_n(\cdot)$ is a smooth function of X and u. To separate u from $g_n(\cdot)$ and then design adaptive controller, the Taylor's theorem in [41] can be applied to decoupling analysis

$$\begin{aligned} g_n(X, u) = g_n(X, 0) &+ \frac{\partial g_n(X, 0)}{\partial u}u + \frac{1}{2!}\frac{\partial^2 g_n(X, 0)}{\partial u^2}u^2 \\ &+ \cdots + \frac{1}{n!}\frac{\partial^n g_n(X, 0)}{\partial u^n}u^n + R_{n+1}(X, u) \end{aligned} \tag{6}$$

where $R_{n+1}(X, u) = [1/(n+1)!][(\partial^{n+1} g_n(X, \xi))/\partial u^{n+1}]u^{n+1}$ with ξ being a constant between 0 and u. Consequently, substituting (6) into (5), it is seen that

$$f_n(X, u) = f_n(X, 0) + g_n(X, 0)u + h_n(X, u) \tag{7}$$

where $h_n(X,u) = [(\partial g_n(X,0))/\partial u]u^2 + (1/2!)[(\partial^2 g_n(X,0))/\partial u^2]u^3 + \cdots + (1/n!)[(\partial^n g_n(X,0))/\partial u^n]u^{n+1} + R_{n+1}(X,u)u$. Now let $C(X) = f_n(X,0) + h_n(X,u)$, this shows that (4) holds. ■

Lemma 2 [40]: For any $\delta > 0$ and $z \in \mathbb{R}$, the following fact holds:

$$0 \le |z| - z\tanh\left(\frac{z}{\delta}\right) \le \kappa\delta \tag{8}$$

with $\kappa = 0.2785$.

Lemma 3 [42]: Assume $q(t)$ is a continuous function defined on $[0,+\infty)$. If $q \in L^2[0,+\infty)$ and $\dot{q} \in L_\infty$, then

$$\lim_{t\to\infty} q(t) = 0. \tag{9}$$

Remark 3: On the basis of backstepping design, Lemmas 1–3 play the important roles in the latter stability analysis for unknown parameter estimation and event-trigger input scheme. To effectively separate the control input u from $f_n(X,u)$, the mean-value theorem and the Taylor expansion method are applied to the decoupling transformation from (1) to (4) in Lemma 1. By Lemmas 2 and 3, the asymptotic tracking control objective can be achieved instead of traditional UUB results.

III. Adaptive Event-Trigger Controller Design

To construct the control input, an efficient adaptive event-triggered controller will be provided based on the backstepping procedure. The design scheme begins with the following error transformations:

$$\begin{aligned} e_1 &= y - y_r \\ e_k &= x_k - u_{k-1}, \quad k = 2,3,\ldots,n-1 \end{aligned} \tag{10}$$

where u_{k-1} is the virtual controller designed in step $k-1$. By this way, the final event-triggered control signal u is generated in the last step.

Step 1: From (10), it is clear that

$$\begin{aligned} \dot{e}_1 &= g_1x_2 + f_1 + \psi_1^T\eta_1 - \dot{y}_r \\ &= g_1e_2 + g_1u_1 + f_1 + \psi_1^T\eta_1 - \dot{y}_r. \end{aligned} \tag{11}$$

To stabilize (11), we choose the following Lyapunov function:

$$V_1 = \frac{1}{2}e_1^2 + \frac{1}{2}\tilde{\Upsilon}_1^T\Gamma_1^{-1}\tilde{\Upsilon}_1 \tag{12}$$

where $\Upsilon_1 = \eta_1$, $\hat{\Upsilon}_1$ is the estimation of Υ_1, $\Gamma_1 = \Gamma_1^T > \mathbf{0}$, and $\tilde{\Upsilon}_1 = \Upsilon_1 - \hat{\Upsilon}_1$ represents the parameter estimation error. From (11), denote $\Psi_1 = \psi_1$, and the time derivative of (12) is

$$\dot{V}_1 = e_1\left(g_1e_2 + g_1u_1 + f_1 + \Psi_1^T\Upsilon_1 - \dot{y}_r\right) - \tilde{\Upsilon}_1^T\Gamma_1^{-1}\dot{\hat{\Upsilon}}_1. \tag{13}$$

Noting Assumption 2, the virtual control u_1 with adaptive law $\hat{\Upsilon}_1$ is now designed as

$$\begin{aligned} u_1 &= g_1^{-1}\left(-a_1e_1 - f_1 - \Psi_1^T\hat{\Upsilon}_1 + \dot{y}_r\right) \\ \dot{\hat{\Upsilon}}_1 &= -\epsilon(t)\Gamma_1\hat{\Upsilon}_1 + \Gamma_1\Psi_1e_1 \end{aligned} \tag{14}$$

where $a > 0$ is a design parameter, $\epsilon(t)$ is such that $\epsilon(t) > 0$ and $\int_0^t \epsilon(s)ds \le \bar{\epsilon}^* < \infty\ \forall t \ge 0$. By substituting (14) into (13), it leads to

$$\dot{V}_1 \le -a_1e_1^2 + g_1e_1e_2 + \epsilon(t)\tilde{\Upsilon}_1^T\hat{\Upsilon}_1. \tag{15}$$

Step k(2≤ k≤ n-1): By recursively utilizing $e_k = x_k - u_{k-1}$, it can be deduced that

$$\begin{aligned} \dot{e}_k &= g_kx_{k+1} + f_k + \psi_k^T\eta_k - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial x_i}\left(x_{i+1} + f_i + \psi_i^T\eta_i\right) \\ &\quad - \sum_{i=0}^{k-1}\frac{\partial u_{k-1}}{\partial y_r^{(i)}}y_r^{(i+1)} - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial\hat{\Upsilon}_i}\dot{\hat{\Upsilon}}_i \\ &= g_kz_{k+1} + g_ku_k + f_k + \Psi_k^T\Upsilon_k - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial x_i}(x_{i+1} + f_i) \\ &\quad - \sum_{i=0}^{k-1}\frac{\partial u_{k-1}}{\partial y_r^{(i)}}y_r^{(i+1)} - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial\hat{\Upsilon}_i}\dot{\hat{\Upsilon}}_i \end{aligned} \tag{16}$$

where $\Psi_k = [-(\partial u_{k-1}/\partial x_1)\psi_1^T, \ldots, -(\partial u_{k-1}/\ \partial x_{k-1})\psi_{k-1}^T, \psi_k^T]^T$ and $\Upsilon_k = [\eta_1^T, \eta_2^T, \ldots, \eta_k^T]^T$. Construct the Lyapunov function candidate as follows:

$$V_k = V_{k-1} + \frac{1}{2}e_k^2 + \frac{1}{2}\tilde{\Upsilon}_k^T\Gamma_k^{-1}\tilde{\Upsilon}_k \tag{17}$$

where $\Gamma_k = \Gamma_k^T > \mathbf{0}$, $\hat{\Upsilon}_k$ is the estimation of Υ_k, and $\tilde{\Upsilon}_k = \Upsilon_k - \hat{\Upsilon}_k$ is the parameter estimation error. Next, the time derivative of (17) is

$$\begin{aligned} \dot{V}_k &= \dot{V}_{k-1} + e_k\Bigg(g_kz_{k+1} + g_ku_k + f_k + \Psi_k^T\Upsilon_k \\ &\qquad - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial x_i}(x_{i+1} + f_i) - \sum_{i=0}^{k-1}\frac{\partial u_{k-1}}{\partial y_r^{(i)}}y_r^{(i+1)} \\ &\qquad - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial\hat{\Upsilon}_i}\dot{\hat{\Upsilon}}_i\Bigg) - \tilde{\Upsilon}_k^T\Gamma_k^{-1}\dot{\hat{\Upsilon}}_k \\ &\le -\sum_{i=1}^{k-1}a_ie_i^2 \\ &\quad + e_k\Bigg(g_kz_{k+1} + g_ku_k + \Psi_k^T\Upsilon_k \\ &\qquad + f_k - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial x_i}(x_{i+1} + f_i) + g_{k-1}e_{k-1} \\ &\qquad - \sum_{i=0}^{k-1}\frac{\partial u_{k-1}}{\partial y_r^{(i)}}y_r^{(i+1)} - \sum_{i=1}^{k-1}\frac{\partial u_{k-1}}{\partial\hat{\Upsilon}_i}\dot{\hat{\Upsilon}}_i\Bigg) \\ &\quad + \epsilon(t)\sum_{i=1}^{k-1}\tilde{\Upsilon}_i^T\hat{\Upsilon}_i - \tilde{\Upsilon}_k^T\Gamma_k^{-1}\dot{\hat{\Upsilon}}_k. \end{aligned} \tag{18}$$

Correspondingly, the virtual control u_k with adaptive law $\hat{\Upsilon}_k$ can be taken as

$$u_k = g_k^{-1}\Bigg(-a_k e_k - f_k - \Psi_k^T \hat{\Upsilon}_k - g_{k-1} e_{k-1} + \sum_{i=1}^{k-1} \frac{\partial u_{k-1}}{\partial x_i}(x_{i+1} + f_i) + \sum_{i=0}^{k-1} \frac{\partial u_{k-1}}{\partial y_r^{(i)}} y_r^{(i+1)} + \sum_{i=1}^{k-1} \frac{\partial u_{k-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i \Bigg)$$

$$\dot{\hat{\Upsilon}}_k = -\epsilon(t)\Gamma_k \hat{\Upsilon}_k + \Gamma_k \Psi_k e_k \tag{19}$$

where $a_k > 0$ is a design parameter.

Using (18), (19) becomes

$$\dot{V}_k \le -\sum_{i=1}^{k} a_i e_i^2 + g_k e_k e_{k+1} + \epsilon(t) \sum_{i=1}^{k} \tilde{\Upsilon}_i^T \hat{\Upsilon}_i. \tag{20}$$

*Step **n**:* Using the transformation $e_n = x_n - u_{n-1}$ and Lemma 1, we infer that

$$\begin{aligned} \dot{e}_n &= g_n(X,0)u + C(X) + \psi_n^T \eta_n + d \\ &\quad - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial x_i}\big(x_{i+1} + f_i + \psi_i^T \eta_i\big) \\ &\quad - \sum_{i=0}^{n-1} \frac{\partial u_{n-1}}{\partial y_r^{(i)}} y_r^{(i+1)} - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i \\ &= g_n(X,0)u + C(X) + \Psi_n^T \Upsilon_n + d \\ &\quad - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial x_i}(x_{i+1} + f_i) \\ &\quad - \sum_{i=0}^{n-1} \frac{\partial u_{n-1}}{\partial y_r^{(i)}} y_r^{(i+1)} - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i \end{aligned} \tag{21}$$

where $\Psi_n = [-(\partial u_{n-1}/\partial x_1)\psi_1^T, \ldots, -(\partial u_{n-1}/\ \partial x_{n-1})\psi_{n-1}^T, \psi_n^T]^T$ and $\Upsilon_n = [\eta_1^T, \eta_2^T, \ldots, \eta_n^T]^T$. Since the continuous function defined in a given compact set Ω_X is always bounded, then we introduce an unknown positive constant B^* such that $|C(X) + d| \le |C(X)| + |d| \le B^*$ for all $X \in \Omega_X$. It is naturally to let $\hat{B}$ be the estimation of B^*, and $\tilde{B} = B^* - \hat{B}$ be the corresponding estimation error, respectively.

We now employ the following Lyapunov function:

$$V_n = V_{n-1} + \frac{1}{2}e_n^2 + \frac{1}{2}\tilde{\Upsilon}_n^T \Gamma_n^{-1} \tilde{\Upsilon}_n + \frac{1}{2}\gamma^{-1}\tilde{B}^2 \tag{22}$$

where $\gamma > 0, \Gamma_n = \Gamma_n^T > \mathbf{0}$ are the design parameters, $\hat{\Upsilon}_n$ is the estimation of Υ_n, and $\tilde{\Upsilon}_n = \Upsilon_n - \hat{\Upsilon}_n$ is the parameter estimation error.

By taking the time derivative of (22), it is easy to see that

$$\begin{aligned} \dot{V}_n &= \dot{V}_{n-1} + e_n\Bigg(g_n(X,0)u + C(X) + \Psi_n^T \Upsilon_n + d \\ &\quad - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial x_i}(x_{i+1} + f_i) - \sum_{i=0}^{n-1} \frac{\partial u_{n-1}}{\partial y_r^{(i)}} y_r^{(i+1)} \\ &\quad - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i \Bigg) - \tilde{\Upsilon}_n^T \Gamma_n^{-1} \dot{\hat{\Upsilon}}_n - \gamma^{-1} \tilde{B}\dot{\hat{B}} \\ &\le -\sum_{i=1}^{n-1} a_i e_i^2 + |e_n| B^* \\ &\quad + e_n\Bigg(g_n(X,0)u + \Psi_n^T \Upsilon_n \\ &\quad - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial x_i}(x_{i+1} + f_i) + g_{n-1} e_{n-1} \\ &\quad - \sum_{i=0}^{n-1} \frac{\partial u_{n-1}}{\partial y_r^{(i)}} y_r^{(i+1)} - \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i \Bigg) \\ &\quad + \epsilon(t) \sum_{i=1}^{n-1} \tilde{\Upsilon}_i^T \hat{\Upsilon}_i - \tilde{\Upsilon}_n^T \Gamma_n^{-1} \dot{\hat{\Upsilon}}_n - \gamma^{-1} \tilde{B}\dot{\hat{B}}. \end{aligned} \tag{23}$$

Hence, we choose the continuous controller as follows:

$$\begin{aligned} u_n &= -a_n e_n - \Psi_n^T \hat{\Upsilon}_n - g_{n-1} e_{n-1} \\ &\quad + \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial x_i}(x_{i+1} + f_i) + \sum_{i=0}^{n-1} \frac{\partial u_{n-1}}{\partial y_r^{(i)}} y_r^{(i+1)} \\ &\quad + \sum_{i=1}^{n-1} \frac{\partial u_{n-1}}{\partial \hat{\Upsilon}_i} \dot{\hat{\Upsilon}}_i - \frac{e_n \hat{B}^2}{e_n \tanh\big(e_n \epsilon^{-1}\big)\hat{B} + \epsilon} \\ \dot{\hat{\Upsilon}}_n &= -\epsilon(t)\Gamma_n \hat{\Upsilon}_n + \Gamma_n \Psi_n e_n \\ \dot{\hat{B}} &= -\gamma\epsilon(t)\hat{B} + \gamma |e_n| \end{aligned} \tag{24}$$

where $a_n > 0$ is a design parameter.

Furthermore, the actual event-triggered control input strategy is given as follows:

$$v(t) = -\rho_0^{-1}(1 + \sigma_0)\Big(u_n \tanh\Big(\frac{u_n e_n}{\epsilon}\Big) + \sigma_1 \tanh\Big(\frac{e_n \sigma_1}{\epsilon}\Big) + e_0 \tanh\Big(\frac{e_0 e_n}{\epsilon}\Big)\Big) \tag{25}$$

$$\begin{aligned} u(t) &= v(t_s) \quad \forall t \in \big[t_s, t_{s+1}\big) \\ t_{s+1} &= \inf\big\{t \in \mathbb{R}^+ \big| |e_u(t)| \ge \sigma_0 |u(t)| + \mu_0 e_0 + \nu_0\big\} \end{aligned} \tag{26}$$

where the input sampling error $e_u(t)$ is denoted as $e_u(t) = v(t) - u(t)$, $e_0 = [1/(\sum_{k=1}^{n} |e_k(t)| + \kappa_0)$, and $\kappa_0 > 0, \rho_0 > 0, 0 < \sigma_0 < 1, \sigma_1 > 0, \mu_0 > 0, \nu_0 > 0$ are positive design parameters such that

$$\rho_0 \le f_l^*, \ \ \mu_0 f_u^* < 1 - \sigma_0, \ \ \nu_0 f_u^* < \sigma_1(1 - \sigma_0). \tag{27}$$

Besides, $t_s, s \in \mathbb{N}^+$ represents the input update time. It means that when the trigger condition (26) is activated, the time will be set as t_{s+1} and then $u(t_{s+1})$ is implemented the controller. Especially, the final input u keeps in a constant value $u(t) = v(t_s)\ \forall t \in [t_s, t_{s+1})$.

Remark 4: It should be pointed out that there is no involving any approximation schemes [7], [15]–[23], [35]. More especially, the tracking errors of the existing results [8], [11], [13] are only UUB rather than asymptotically converge to zero, In this article, the augmented dimension adaptive control laws and the online updated estimation of the compounded disturbance bound with a positive continuous integrable function are effectively constructed. Moreover, by using the Taylor theorem, a novel nonaffine nonlinear decoupling strategy is proposed to guarantee the tracking errors to be zero asymptotically.

Remark 5: Different form the event-triggering schemes in [36], an improved adaptive event-triggered design strategy by introducing a decreasing function on the basis of the relative threshold method is proposed here. Note that the introduced decreasing function $e_0(t)$ provides a larger triggering threshold when the tracking error e_k becomes small for $k = 1, 2, \ldots, n$. By adding the function e_0 with the variables of tracking errors, we can obtain the desired asymptotic tracking performance if the fixed threshold ν_0, and the adjustable parameters κ_0, μ_0, and σ_0 of $|e_0|$ and $|u|$, respectively, are properly chosen.

By means of (25) and (26), it is easy to see that $|v(t) - u(t)| \le \sigma_0|u(t)| + \mu_0 e_0 + \nu_0 \; \forall t \in [t_s, t_{s+1})$. Meanwhile, we can also obtain that there exists a continuous function $\chi_0(t)$ satisfying $v(t) - u(t) = \chi_0(t)(\sigma_0|u(t)| + \mu_0 e_0(t) + \nu_0)$ with $\chi_0(t_s) = 0$, $\chi_0(t_{s+1}) = \pm 1$, $|\chi_0(t)| \le 1$ for all $t \in [t_s, t_{s+1})$ as in [36]. Then, we have

$$u(t) = \frac{v(t) - \chi_0(t)\mu_0 e_0 - \chi_0(t)\nu_0}{1 + \chi_1(t)\sigma_0} \tag{28}$$

where $\chi_1(t) = \pm\chi_0(t)$ and $|\chi_1(t)| \le 1$. Recalling that $-x\tanh(x/\kappa) \le 0 \; \forall x \in \mathbb{R}, \kappa > 0$, we find that $e_n v(t) \le 0$. Thus, it can be further established

$$\frac{e_n v(t)}{(1 + \chi_1(t)\sigma_0)} \le \frac{e_n v(t)}{(1 + \sigma_0)} \tag{29}$$

Using (23), (24), and (27)–(29), it is seen from Assumption 2 and Lemma 2 that

$$\begin{aligned}\dot{V}_n \le & -\sum_{i=1}^{n} a_i e_i^2 - |e_0||e_n| - \sigma_1|e_n| + \frac{f_u^*\mu_0|e_0||e_n|}{1-\sigma_0} \\ & + \frac{f_u^*\nu_0|e_n|}{1-\sigma_0} + \epsilon(t)\sum_{i=1}^{n}\tilde{\Upsilon}_i^T\hat{\Upsilon}_i + \epsilon(t)\tilde{B}\hat{B} + 1.8355\epsilon(t) \\ \le & -\sum_{i=1}^{n} a_i e_i^2 + \epsilon(t)\sum_{i=1}^{n}\tilde{\Upsilon}_i^T\hat{\Upsilon}_i + \epsilon(t)\tilde{B}\hat{B} + 1.8355\epsilon(t).\end{aligned} \tag{30}$$

Now, we will give the main result of the asymptotic stabilization-based event-triggered of the closed-loop systems. Also, the existence of the lower bound of inter-event intervals $\{t_{s+1} - t_s\}$ will be studied by the following theorem.

Theorem 1: Consider the nonaffine nonlinear systems (1) subject to event-triggered inputs, and Assumptions 1 and 2 hold. Suppose that $X(0) \in \Omega_X = \{X||x_1(0)| \le C_1^*, \ldots, |x_n(0)| \le C_n^*\}$ with $C_i^* > 0$ being a bound of x_i for $i = 1, 2, \ldots, n$. Then, the presented control scheme (14), (19), and (24)–(26) can ensure that all the tracking errors $e_k, k = 1, 2, \ldots, n$ asymptotically converge to zero over Ω_X, and the inter-execution intervals $\{t_{s+1} - t_s\}$ are lower bounded by a positive constant.

Proof: Notice that the fact $\tilde{\Upsilon}_i^T\hat{\Upsilon}_i = \tilde{\Upsilon}_i^T(\Upsilon_i - \tilde{\Upsilon}_i) \le (1/4)\|\Upsilon_i\|^2, i = 1, 2, \ldots, n, \tilde{B}\hat{B} = \tilde{B}(B^* - \tilde{B}) \le (1/4)B^{*2}$, we then have

$$\dot{V}_n \le -a_0\|e\|^2 + \frac{1}{4}\epsilon(t)\left(\sum_{i=1}^{n}\|\Upsilon_i\|^2 + B^{*2} + 7.342\right) \tag{31}$$

where $a_0 = \min\{a_i, i = 1, 2, \ldots, n\}$, $e = [e_1, e_2, \ldots, e_n]^T$. For the further analysis, we can rephrase an augmented dimension error vector satisfying $\tilde{e} = [e^T, \tilde{\Upsilon}_1^T, \ldots, \tilde{\Upsilon}_n^T, \tilde{B}]^T$, and then integrating (31) from 0 to t yields

$$V_n(\tilde{e}) \le -a_0\int_0^t \|e(\tau)\|^2 d\tau + V_n(\tilde{e}(0)) + b_0 \tag{32}$$

for the positive constant b_0 satisfying $b_0 = (1/4)\bar{\epsilon}^*(\sum_{i=1}^{n}\|\Upsilon_i\|^2 + B^{*2} + 7.342)$.

By recursively inferring, (32) shows that $V_n(\tilde{e})$ and hence $e, \tilde{\Upsilon}_i, i = 1, 2, \ldots, n, \tilde{B}, u$ are all bounded in the preset compact set Ω_X. This implies $\dot{e}$ is also bounded. From Lemma 3 and (32), It is not hard to deduce that $e \in L^2$ and $\lim_{t\to\infty}\|e\| = 0$.

Next, the existence of the lower bound $\bar{T}^* > 0$ of inter-event intervals $\{t_{s+1} - t_s\}$ is to be proved. By computing the time derivative of $e_u(t) = v(t) - u(t) \; \forall t \in [t_s, t_{s+1})$, we then infer that

$$\frac{d}{dt}|e_u| = \frac{d}{dt}(e_u * e_u)^{\frac{1}{2}} = \mathrm{sign}(e_u)\dot{e}_u \le |\dot{v}|. \tag{33}$$

It follows from (25) that $\dot{v}$ is also continuous in Ω_X. Therefore, we can conclude $|\dot{v}| < \bar{V}^*$ with $\bar{V}^* > 0$ being a local upper bound. From $e_u(t_s) = 0$ and $\lim_{t\to t_{s+1}} e_u(t) = \sigma_0|u(t_{s+1})| + \mu_0 e_0(t_{s+1}) + \nu_0$, the lower bound $\bar{T}^*$ of inter-event intervals can be found and it satisfies that $\bar{T}^* \ge [(\sigma_0|u(t_{s+1})| + \mu_0 e_0(t_{s+1}) + \nu_0)/\bar{V}^*] \ge (\nu_0/\bar{V}^*)$, which implies the Zeno behavior cannot occur [39]. Theorem 1 holds true. ■

Remark 6: Based on the above analysis, a new adaptive event-trigger asymptotic tracking control strategy of uncertain nonlinear systems with unknown parameter vectors can be obtained. Correspondingly, the designed adaptive controllers (14), (19), (24), and (25) with triggering mechanism (26) not only guarantees that all the signals in the closed-loop systems are locally bounded, and the system output tracking error can asymptotically converge to zero, but also the communication load can be effectively reduced.

IV. Simulation Results

To verify the proposed approach, an event-triggered adaptive controller design problem of inverted pendulum system is studied in this section. The corresponding nonaffine nonlinear dynamics model [43] is described by

$$\begin{aligned}\dot{x}_1 &= x_2 + \psi_1\eta_1 \\ \dot{x}_2 &= l_1\sin(x_1) + l_2 x_2 + l_3(0.5u + \tanh(u)) \\ &\quad + \psi_2\eta_2 + d \\ y &= x_1\end{aligned} \tag{34}$$

where x_1 and x_2 are the system states, $l_1 = 24.527, l_2 = -0.107, l_3 = 12.5$, $\psi_1 = x_1^2, \psi_2 = x_2^2$, η_1 and η_2 denote the unknown parameter uncertainties, $d = 0.8\cos(t)$, and the reference trajectory is $y_r = 0.5\sin(t)$. By using the event-triggered adaptive control (14), (19), and (24)–(26), we choose the simulation parameters as $a_1 = a_2 = 20, \Gamma_1 = 15, \Gamma_2 = \begin{bmatrix} 15 & 0 \\ 0 & 15 \end{bmatrix}, \gamma = 18, \epsilon(t) = e^{-0.02t}, \rho_0 = f_l^* = f_u^* = 1.5l_3 = 18.75, \sigma_0 = 0.6, \sigma_1 = 5, \mu_0 = 0.02$, and $\nu_0 = 0.1$. Let the initial values be $X(0) = [-0.1, 0.1]^T$, $\hat{\Upsilon}_1(0) = 0.5$, $\hat{\Upsilon}_2(0) =$

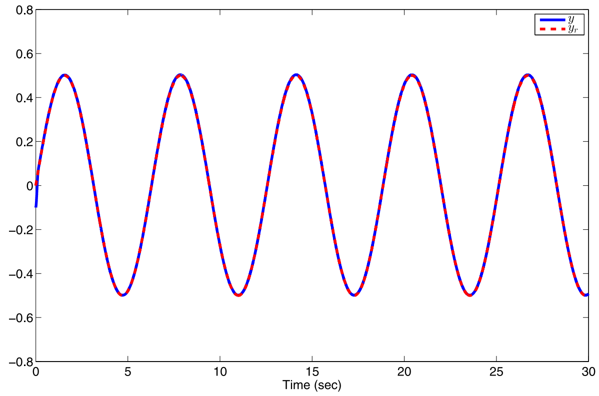


Fig. 1. Trajectories of y and y_r.

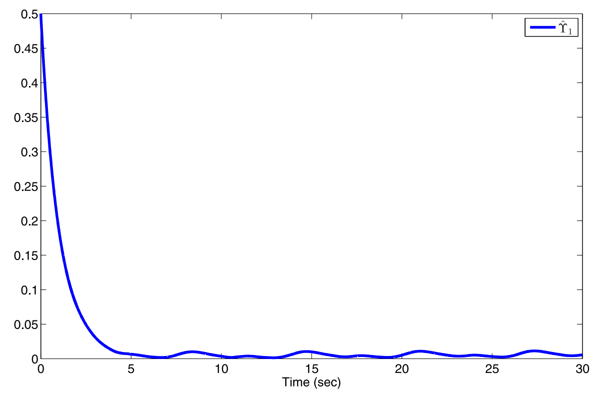


Fig. 2. Adaptive law $\hat{\Upsilon}_1$.

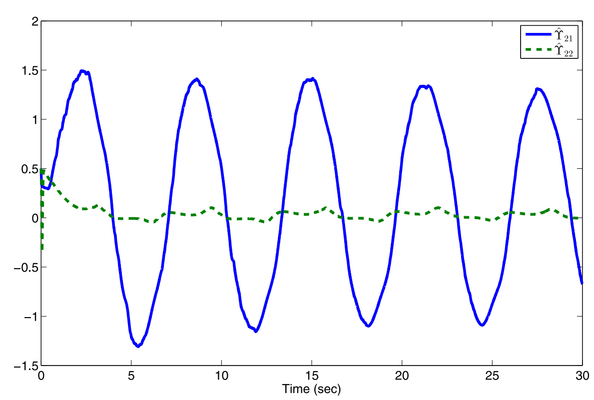


Fig. 3. Adaptive laws $\hat{\Upsilon}_{21}$ and $\hat{\Upsilon}_{22}$.

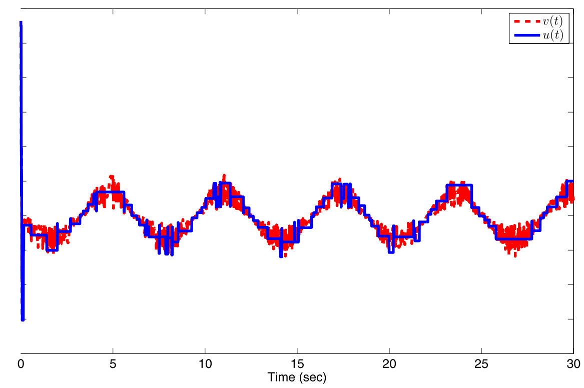


Fig. 4. Trajectories of v and u.

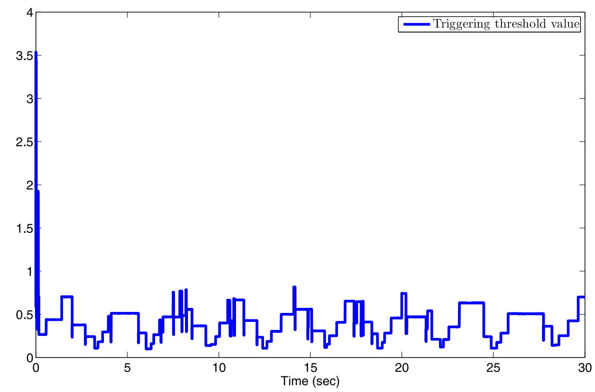


Fig. 5. Triggering threshold value.

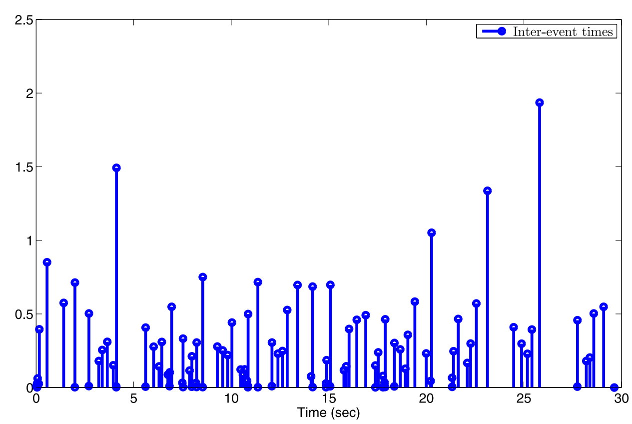


Fig. 6. Inter-event times of u.

$[0.5, 0.5]^T$, and $\hat{B}(0) = 0.5$. Concomitantly, we get the simulation results in Figs. 1–6. In Fig. 1, the trajectories of the system output y and the reference signal y_r are provided. The adaptive estimation curves $\hat{\Upsilon}_1$, $\hat{\Upsilon}_{21}$, $\hat{\Upsilon}_{22}$ and the input signals $u(t)$ and $v(t)$ are shown in Figs. 2–4, respectively. It is clearly seen that they are all bounded. The trajectory of triggering threshold value is provided in Fig. 5, and the numbers of triggering events are 110 in Fig. 6. In view of Figs. 1–6, we can see that both the asymptotic tracking performance and the desired event-triggering utility of the closed-loop nonlinear system are guaranteed in the presence of unknown parameter vectors, external disturbances, and event-triggering inputs. In particular, the numbers of triggering events of the three threshold strategies in [36] are 622, 396, and 347, respectively. This shows the effectiveness of the proposed scheme in this article to reduce the number of triggering transmissions control in comparison with the existing methods.

V. Conclusion

In this article, the adaptive event-triggered asymptotic tracking control of nonaffine nonlinear systems with unknown parameter vectors is studied. By utilizing the Taylor expansion technique, a new nonaffine nonlinear control input decoupling strategy is proposed, and then the augmented dimension parameter updated laws and the unknown bound estimation of the compounded disturbance are constructed. Moreover, an improved event-trigger mechanism by introducing a decreasing function of tracking error variables is designed. The communication load can be substantially reduced. It is proved that all the closed-loop signals are locally uniformly bounded, and the system output tracking error can converge to zero. The validity of the proposed method is confirmed by a numerical example. In our next work, the adaptive event-triggered tracking control problem with prescribed performance for uncertain nonlinear systems will be further considered.

REFERENCES

[1] G. D. Zong, W. H. Qi, and H. R. Karimi, "L_1 control of positive semi-Markov jump systems with state delay," *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Mar. 24, 2020, doi: 10.1109/TSMC.2020.2980034.

[2] G. D. Zong, Y. K. Li, and H. B. Sun, "Composite anti-disturbance resilient control for Markovian jump nonlinear systems with general uncertain transition rate," *Sci. China Inf. Sci.*, vol. 62, no. 2, pp. 022205:1–022205:18, Feb. 2019.

[3] Y. Liu, X. P. Liu, Y. W. Jing, H. Q. Wang, and X. H. Li, "Annular domain finite-time connective control for large-scale systems with expanding construction," *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Jan. 6, 2020, doi: 10.1109/TSMC.2019.2960009.

[4] J. X. Dong, Q. H. Hou, and M. M. Ren, "Control synthesis for discrete-time T-S fuzzy systems based on membership function-dependent H_∞ performance," *IEEE Trans. Fuzzy Syst.*, early access, Nov. 1, 2019, doi: 10.1109/TFUZZ.2019.2950879.

[5] B. Niu, Y. J. Liu, W. L. Zhou, H. T. Li, P. Y. Duan, and J. Q. Li, "Multiple Lyapunov functions for adaptive neural tracking control of switched nonlinear nonlower-triangular systems," *IEEE Trans. Cybern.*, vol. 50, no. 5, pp. 1877–1886, May 2020.

[6] M. Krstic, I. Kanellakopoulos, and P. Kokotovic, *Nonlinear and Adaptive Control Design*. New York, NY, USA: Wiley, 1995.

[7] S. S. Ge, F. Hong, and T. H. Lee, "Adaptive neural network control of nonlinear systems with unknown time delays," *IEEE Trans. Autom. Control*, vol. 48, no. 11, pp. 2004–2010, Nov. 2003.

[8] C. C. Hua, X. P. Guan, and P. Shi, "Robust backstepping control for a class of time delayed systems," *IEEE Trans. Autom. Control*, vol. 50, no. 6, pp. 894–899, Jun. 2005.

[9] D. P. Li, C. L. P. Chen, Y.-J. Liu, and S. C. Tong, "Neural network controller design for a class of nonlinear delayed systems with time-varying full-state constraints," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 9, pp. 2625–2636, Sep. 2019.

[10] X. Yang, H. B. He, and D. R. Liu, "Event-triggered optimal neuro-controller design with reinforcement learning for unknown nonlinear systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 9, pp. 1866–1878, Sep. 2019.

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

[12] Z. Q. Zhang, S. Y. Xu, and B. Y. Zhang, "Asymptotic tracking control of uncertain nonlinear systems with unknown actuator nonlinearity," *IEEE Trans. Autom. Control*, vol. 59, no. 5, pp. 1336–1341, May 2014.

[13] J.-X. Zhang and G.-H. Yang, "Prescribed performance fault-tolerant control of uncertain nonlinear systems with unknown control directions," *IEEE Trans. Autom. Control*, vol. 62, no. 12, pp. 6529–6535, Dec. 2017.

[14] H. F. Min, S. Y. Xu, B. Y. Zhang, and Q. Ma, "Output-feedback control for stochastic nonlinear systems subject to input saturation and time-varying delay," *IEEE Trans. Autom. Control*, vol. 64, no. 1, pp. 359–364, Jan. 2019.

[15] H. Q. Wang, B. Chen, X. P. Liu, K. F. Liu, and C. Liu, "Robust adaptive fuzzy tracking control for pure-feedback stochastic nonlinear systems with input constraints," *IEEE Trans. Cybern.*, vol. 43, no. 6, pp. 2093–2104, Dec. 2013.

[16] X. D. Zhao, H. J. Yang, W. G. Xia, and X. Y. Wang, "Adaptive fuzzy hierarchical sliding-mode control for a class of MIMO nonlinear time-delay systems with input saturation," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 5, pp. 1062–1077, Oct. 2017.

[17] C. G. Liu, H. Q. Wang, X. P. Liu, and Y. C. Zhou, "Adaptive finite-time fuzzy funnel control for nonaffine nonlinear systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Jun. 4, 2019, doi: 10.1109/TSMC.2019.2917547.

[18] X. D. Zhao, L. Ma, G. Zong, and X. Y. Wang, "Fuzzy approximation based asymptotic tracking control for a class of uncertain switched nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 4, pp. 632–644, Apr. 2020.

[19] L.-B. Wu and J. H. Park, "Adaptive fault-tolerant control of uncertain switched nonaffine nonlinear systems With actuator faults and time delays," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 50, no. 9, pp. 3470–3480, Sep. 2020.

[20] M. Chen and S. S. Ge, "Direct adaptive neural control for a class of uncertain nonaffine nonlinear systems based on disturbance observer,," *IEEE Trans. Cybern.*, vol. 43, no. 4, pp. 1213–1225, Aug. 2013.

[21] J. H. Qin, G. S. Zhang, W. X. Zheng, and Y. Kang, "Neural network-based adaptive consensus control for a class of nonaffine nonlinear multiagent systems with actuator faults," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 12, pp. 3633–3644, Dec. 2019.

[22] L. Ma, N. Xu, X. D. Zhao, G. D. Zong, and X. Huo, "Small-gain technique-based adaptive neural output-feedback fault-tolerant control of switched nonlinear systems with unmodeled dynamics," *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Feb. 6, 2020, doi: 10.1109/TSMC.2020.2964822.

[23] Y.-X. Li and G.-H. Yang, "Adaptive neural control of pure-feedback nonlinear systems with event-triggered communications," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 12, pp. 6242–6251, Dec. 2018.

[24] P. Tabuada, "Event-triggered real-time scheduling of stabilizing control tasks," *IEEE Trans. Autom. Control* , vol. 52, no. 9, pp. 1680–1685, Sep. 2007.

[25] D. Yue, E. G. Tian, and Q. L. Han, "A delay system method for designing event-triggered controllers of networked control systems," *IEEE Trans. Autom. Control*, vol. 58, no. 2, pp. 475–481, Feb. 2013.

[26] R. Postoyan, P. Tabuada, D. Nešić, and A. Anta, "A framework for the event-triggered stabilization of nonlinear systems," *IEEE Trans. Autom. Control*, vol. 60, no. 4, pp. 982–996, Apr. 2015.

[27] Y.-X. Li, G.-H. Yang, and S. C. Tong, "Fuzzy adaptive distributed event-triggered consensus control of uncertain nonlinear multiagent systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 9, pp. 1777–1786, Sep. 2019.

[28] D. Y. Yao, H. Y. Li, R. Q. Lu, and Y. Shi, "Distributed sliding-mode tracking control of second-order nonlinear multiagent systems: An event-triggered approach," *IEEE Trans. Cybern.*, vol. 50, no. 9, pp. 3892–3902, Sep. 2020.

[29] H. Ma, H. Y. Li, R. Q. Lu, and T. W. Huang, "Adaptive event-triggered control for a class of nonlinear systems with periodic disturbances," *Sci. China Inf. Sci.*, vol. 63, no. 5, May 2020, Art. no. 150212.

[30] Q. Zhou, G. D. Chen, R. Q. Lu, and W. W. Bai, "Disturbance-observer-based event-triggered control for multi-agent systems with input saturation," *Sci. China Inf. Sci.*, vol. 49, no. 11, pp. 1502–1516, Nov. 2019.

[31] H. J. Liang, X. Y. Guo, Y. N. Pan, and T. W. Huang, "Event-triggered fuzzy bipartite tracking control for network systems based on distributed reduced-order observers (Revised manuscript of TFS-2019-1049)," *IEEE Trans. Fuzzy Syst.*, early access, Mar. 23, 2020, doi: 10.1109/TFUZZ.2020.2982618.

[32] Q. Zhou, W. Wang, H. J. Liang, M. Basin, and B. H. Wang, "Observer-based event-triggered fuzzy adaptive bipartite containment control of multi-agent systems with input quantization," *IEEE Trans. Fuzzy Syst.*, early access, Nov. 15, 2019, doi: 10.1109/TFUZZ.2019.2953573.

[33] Z. C. Zhu, Y. N. Pan, Q. Zhou, and C. X. Lu, "Event-triggered adaptive fuzzy control for stochastic nonlinear systems with unmeasured states and unknown backlash-like hysteresis," *IEEE Trans. Fuzzy Syst.*, early access, Feb. 13, 2020, doi: 10.1109/TFUZZ.2020.2973950.

[34] H. L. Ren, G. D. Zong, and H. R. Karimi, "Asynchronous finite-time filtering of networked switched systems and its application: An event-driven method," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 66, no. 1, pp. 391–402, Jan. 2019.

[35] Q.-Y. Fan and G.-H. Yang, "Event-based fuzzy adaptive fault-tolerant control for a class of nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 5, pp. 2686–2698, Oct. 2018.

[36] L. T. Xing, C. Y. Wen, Z. T. Liu, H. Y. Su, and J. P. Cai, "Event-triggered adaptive control for a class of uncertain nonlinear systems," *IEEE Trans. Autom. Control*, vol. 62, no. 4, pp. 2071–2076, Apr. 2017.

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

[38] L. Cao, Q. Zhou, G. W. Dong, and H. Y. Li, "Observer-based adaptive event-triggered control for nonstrict-feedback nonlinear systems with output constraint and actuator failures," *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Mar. 8, 2019, doi: 10.1109/TSMC.2019.2895858.

[39] K. H. Johansson, M. Egerstedt, J. Lygeros, and S. Sastry, "On the regularization of Zeno hybrid automata," *Syst. Control Lett.*, vol. 38, no. 3, pp. 141–150, Oct. 1999.

[40] M. M. Polycarpou, "Stable adaptive neural control scheme for nonlinear systems," *IEEE Trans. Autom. Control*, vol. 41, no. 3, pp. 447–451, Mar. 1996.

[41] R. Bartle, *The Elements of Real Analysis*. Hoboken, NJ, USA: Wiley, 1964.

[42] G. Tao, S. H. Chen, X. D. Tang, and S. M. Joshi, *Adaptive Control Design and Analysis*. New York, NY, USA: Wiley, 2003.

[43] T. Bian, Y. Jiang, and Z.-P. Jiang, "Adaptive dynamic programming and optimal control of nonlinear nonaffine systems," *Automatica*, vol. 50, no. 10, pp. 2624–2632, Oct. 2014.

Li-Bing Wu was born in Chaoyang, China, in 1980. He received the B.S. degree in mathematics and applied mathematics from Jinzhou Normal College, Jinzhou, China, in 2004, the M.S. degree in basic mathematics from Northeastern University, Shenyang, China, in 2007, and the Ph.D. degree in control theory and control engineering from Northeastern University, Shenyang, China, in 2016.

He was a Postdoctoral Fellow with Yeungnam University, Kyongsan, South Korea, from 2018 to 2019. He is currently an Associate Professor with the School of Science, University of Science and Technology Liaoning, Anshan, China. His research interests include adaptive control, fault-tolerant control, nonlinear control, and fault estimation.

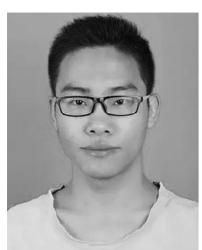
Ju H. Park (Senior Member, IEEE) received the Ph.D. degree in electronics and electrical engineering from the Pohang University of Science and Technology (POSTECH), Pohang, South Korea, in 1997.

From May 1997 to February 2000, he was a Research Associate with the Engineering Research Center–Automation Research Center, POSTECH. In March 2000, he joined Yeungnam University, Kyongsan, South Korea, where he is currently the Chuma Chair Professor. He has coauthored the monograph *Recent Advances in Control and Filtering of Dynamic Systems With Constrained Signals* (New York, NY, USA: Springer-Nature, 2018) and *Dynamic Systems With Time Delays: Stability and Control* (New York, NY, USA: Springer-Nature, 2019), and is an Editor of an edited volume *Recent Advances in Control Problems of Dynamical Systems and Networks* (New York: Springer-Nature, 2020). His research interests include robust control and filtering, neural/complex networks, fuzzy systems, multiagent systems, and chaotic systems. He has published a number of articles in the above areas.

Prof. Park has been a recipient of the Highly Cited Researchers Award by Clarivate Analytics (formerly, Thomson Reuters) since 2015, and listed in three fields, Engineering, Computer Sciences, and Mathematics, in 2019 and 2020. He also serves as an Editor for the *International Journal of Control, Automation and Systems*. He is also a Subject Editor/Advisory Editor/Associate Editor/Editorial Board Member of several international journals, including *IET Control Theory & Applications*, *Applied Mathematics and Computation*, *Journal of the Franklin Institute*, *Nonlinear Dynamics*, *Engineering Reports*, *Cogent Engineering*, the IEEE TRANSACTIONS ON FUZZY SYSTEMS, IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, and IEEE TRANSACTIONS ON CYBERNETICS. He is a Fellow of the Korean Academy of Science and Technology.

Xiang-Peng Xie (Member, IEEE) received the B.S. and Ph.D. degrees in control theory and control engineering from Northeastern University, Shenyang, China, in 2004 and 2010, respectively.

From 2012 to 2014, he was a Postdoctoral Fellow with the Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, China. He is currently a Professor with the Department of Intelligent Control, Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include fuzzy modeling and control synthesis, state estimations, optimization in process industries, and intelligent optimization algorithms.



Ya-Feng Li received the B.S. degree from the Hebei University of Science and Technology, Shijiazhuang, China, in June 2013, and the Ph.D. degree from Yanshan University, Qinhuangdao, China, in January 2019.

He worked as a Research Associate with the City University of Hong Kong, Hong Kong, in 2018 and as a Postdoctoral Fellow with Yeungnam University, Gyeongsan, South Korea, from 2019 to 2020. His current research interests include robust control, adaptive control, fault-tolerant control, nonlinear system control, and multiagent systems.

Dr. Li is a Reviewer of the IEEE TRANSACTIONS ON CYBERNETICS, *IEEE/ASME Transactions on Mechatronics*, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, *International Journal of Robust and Nonlinear Control*, *Journal of the Franklin Institute*, and *Nonlinear Dynamics*.