Event-triggered neuroadaptive output-feedback control for nonstrict-feedback nonlinear systems with given performance specifications

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Abstract This paper focuses on the event-triggered neuroadaptive output-feedback tracking control issue for nonstrict-feedback nonlinear systems with given performance specifications. By constructing a neural observer to estimate unmeasurable states, a novel event-triggered controller is presented together with a piecewise threshold rule. The presented event-triggered mechanism has two thresholds to reduce communication resources between the controller and actuator. An improved speed transformation function is introduced to make the output tracking error converge to a preassigned small region at predesigned converging mode within preset finite time. Combining the variable separation method based on the structural property of radial basis function (RBF) and backstepping technology, the algebraic loop problem caused by the nonstrict-feedback structure is overcome. The command filtered technology with filtering error compensating signal is applied to address the “explosion of complexity” problem. Furthermore, Lyapunov stability analysis demonstrates that under the presented event-triggered controller, all signals in the closed-loop system are semiglobally bounded, and the Zeno-behaviour is ruled out

strictly. Numerical simulations are finally provided to illustrate the presented control scheme.

Keywords Nonstrict-feedback nonlinear systems · Adaptive neural control · Given performance specifications · Speed transformation function · Event-triggered control · Command filtered backstepping

1 Introduction

Adaptive backstepping technology has become a resultful instrument to design the control scheme for uncertain strict-feedback systems, and a lot of significant research results have been achieved (see [1]–[7]). Whereas many practical engineering systems, such as the helicopter model [8], the ball and beam system [9], and uncertain robot systems [10], are in nonstrict-feedback form. The algebraic loop problem, caused by the nonstrict-feedback structure, will render the traditional adaptive backstepping control method discussed in strict-feedback systems invalid. Thus, to solve this problem, the Butterworth low-pass filter was adopted in [11]–[12] for pure-feedback nonlinear systems. During the control law design process, it is known that the introduction of additional low-pass filter will inevitably lead to the increase in algorithm complexity. Without introducing the additional filter, some adaptive neural networks/fuzzy control strategies were developed in [13]–[16] for nonstrict-feedback nonlinear systems via utilizing the variable separation technology. The restrictive condition, requiring the unknown functions to conform to the monotonically increasing property [13]–[16], was overcome in [17]–[18] according to the structural property of fuzzy-logic systems or neural networks. Such results were further generalized to the cases of prescribed performance control and finite-time control. To ensure that the tracking error enters into a prescribed range, an adaptive fuzzy controller was constructed in [19] for nontriangular

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nonlinear systems, in which the tracking error with constraint was converted into a new variable. Via applying a fuzzy observer to estimate unmeasurable states, authors in [20] investigated the finite-time adaptive control issue for nonlinear systems in nontriangular form, where the dynamic surface control scheme was adopted to overcome the “explosion of complexity” problem resulted from the iterative differentiations for virtual control functions.

Although the prescribed performance control can achieve that the output error enters into a predefined compact set at the prescribed converging mode [21]–[23], it cannot guarantee that the convergence of output error is realized in a finite time. In order for the tracking error to converge within a finite time, the finite-time controller in [24]–[26] attempts to give a new idea, but the settling time, depending on the initial condition of system states, cannot be given arbitrarily and chosen in advance. Fortunately, the work [27] applied a speed function to transform the original output error into an accelerated one, and then the convergence performance of original output error can be adjusted via stabilizing the accelerated dynamic system. This idea was further extended in [28] to design prescribed performance controller for MIMO strict-feedback systems, where the tracking error can converge to a preassigned compact set in a pre-given time. More recently, via blending finite-time performance function and intermediate transformation, the finite-time controller with prescribed performance was presented for nonlinear strict-feedback systems in [29]–[31] and for nonlinear nonstrict-feedback systems in [32], respectively. However, the results presented in [27]–[32] are dependent on the full-state information, and do not take into account the event-triggered control issue.

Due to the increasing popularity of the network control, event-triggered scheme has been widely acknowledged as an effective alternative to traditional periodic sampling scheme, which can greatly reduce transmission burden in the communication network. Thus, some significant results about event-triggered control scheme can be found in [33]–[35]. Among them, the authors in [33] developed an output-feedback controller with prescribed performance for pure-feedback systems using the fixed threshold event-triggered mechanism. It should be noted that the threshold value in [33] does not change during the control process. For further decreasing the data transmission and increasing the efficiency in resource utilization, an event-triggered adaptive controller was designed in [34] for strict-feedback systems with actuator failures by utilizing the neural state observer, where a varying threshold method, in the light of the value of control signal, was proposed to update the control signal. Based on the linear state observer, an event-triggered adaptive neural network controller was proposed in [35] for nonstrict-feedback systems with unknown control directions via adopting relative threshold strategy. However, the complexity of the event-

triggered control algorithm based on relative threshold will increase in order to guarantee the stability of whole system because the triggering condition contains the control signal.

According to the discussions above, it is very necessary to develop a new event-triggered neuroadaptive output-feedback controller with given performance specifications for nonstrict-feedback uncertain nonlinear systems, which drives the current work. Specifically, there are three complicated problems to be solved in the article:

- 1) How to use a speed transformation function to design an event-triggered output-feedback controller with given performance specifications for nonstrict-feedback uncertain nonlinear systems?
- 2) How to effectively reduce data transmission and improve resource utilization while avoiding the inclusion of control signal in the triggering condition?
- 3) How to introduce command filtering technology with filtering error compensating signal to deal with the “explosion of complexity” problem during the control strategy design process?

In this work, a new event-triggered adaptive control scheme combined with neural state observer and command filtering technology will be investigated for nonstrict-feedback uncertain nonlinear systems with given performance specifications. Furthermore, the variable separation method and backstepping technology will be adopted to deal with the algebraic loop problem arising from nonstrict-feedback structure. The main features and contributions of the proposed controller lie in the following aspects:

- 1) In comparison to the observer-based finite-time adaptive tracking control in [4] and [20], observer-based prescribed performance tracking control in [36], the proposed output-feedback control scheme can ensure that not only the tracking error enters into the prescribed bounded set within a preset time, but also decay rate during the preset time interval is predesigned and controllable explicitly. Further, the preset time is independent of the initial condition of system states.
- 2) In comparison to the speed transformation function-based tracking control strategy with given performance specifications in [27] and [28], finite-time tracking control strategy with prescribed performance in [31] for strict-feedback nonlinear systems, this paper applies the output information and universal approximation ability of neural networks to construct state observer, and a novel event-triggered tracking controller is presented for more general nonstrict-feedback nonlinear systems.

- 3) Compared with the event-triggered prescribed performance controller using the fixed threshold strategy in [33] for pure-feedback nonlinear systems, the designed event-triggered mechanism has two thresholds, which can effectively reduce the data transmission and avoid including the control signal in the trigger condition. Furthermore, the com-

mand filtering technology is employed to deal with the “explosion of complexity” and “filtering error compensation” problem by utilizing filtering error compensating signal.

2 Problem formulation

2.1 System description

Consider the following uncertain nonstrict-feedback system:

$$\begin{cases} \dot{x}_k = x_{k+1} + h_k(X), & k = 1, 2, \dots, n-1 \\ \dot{x}_n = u + h_n(X) \\ y = x_1 \end{cases} \quad (1)$$

where $X = [x_1, \dots, x_n]^T \in R^n$ and $u \in R$ represent plant state vector and control input, respectively. $y \in R$ is the output of plant. $h_k(X)$, $k = 1, 2, \dots, n$ represent unknown smooth nonlinear functions. It is assumed that nonstrict-feedback system (1) is completely observable and controllable and only system output y can be directly measured.

Remark 1 Because the nonlinear function $h_k(X)$ in each subsystem contains the whole plant state vector $X = [x_1, \dots, x_n]^T$, the plant (1) is a nonstrict-feedback system. It is worth noting that the control methods developed in [5] and [31] are effective for strict-feedback systems with full-state information. If the backstepping technology in [5] and [31] is adopted to develop control law for nonstrict-feedback system (1), the algebraic loop problem will arise, making it very difficult to design virtual controller. In practice, many practical plants are with nonstrict-feedback structure and unmeasured states. Therefore, the system (1) considered in the article is very necessary.

The purpose of this paper is to present an event-triggered neuroadaptive output-feedback control scheme with given performance specifications for (1), such that:

- 1) All signals in the closed-loop system are semiglobally bounded.
- 2) The tracking error $\chi_1 = y - y_d$, where y_d is the desired reference signal, converges to a prescribed compact set at predesigned decay rate within a pre-given finite time.
- 3) A novel event-triggered mechanism is designed to effectively reduce data transmission between the controller and actuator and the Zeno behaviour is strictly ruled out.

To achieve the control objective, we require the following assumption and lemmas.

Assumption 1 The desired reference signal y_d and its time derivative $\dot{y}_d$ are smooth, bounded, and available.

Remark 2 Compared with traditional backstepping method, the control scheme in this article does not have strict requirements on the desired reference signal, because only the information of y_d and $\dot{y}_d$ is used in the design process.

Lemma 1 [37] For hyperbolic tangent function $\tanh(\cdot)$, the following property holds

$$0 \leq -\hbar \tanh\left(\frac{\hbar}{\varpi}\right) + |\hbar| \leq 0.2785\varpi \quad (2)$$

where $\varpi > 0$, $\hbar \in R$, $-\hbar \tanh(\hbar/\varpi) \leq 0$.

Lemma 2 [38] Consider a continuous nonlinear function $h(X)$ defined on a compact set Ω . Then for $\forall \varepsilon > 0$, there exists a RBF neural network satisfying

$$\sup_{x \in \Omega} |h(X) - \theta^T \phi(X)| \leq \varepsilon \quad (3)$$

where $\theta = [\theta_1, \dots, \theta_M]^T$ represents the ideal weight vector, $\phi(X) = [p_1(X), \dots, p_M(X)]^T$ denotes the basis function vector, $M > 1$ is node number of neural network, and $p_k(X)$ is constructed as $p_k(X) = \exp\left[-(X - v_k)^T(X - v_k)/\gamma_k^2\right]$, $k = 1, 2, \dots, M$, $v_k = [v_{k1}, \dots, v_{kn}]^T$ is the center vector and γ_k is the width of Gaussian function.

Remark 3 According to the definition of $p_k(X)$ and $\phi(X)$, it can be demonstrated that $0 < p_k(X) \leq 1$ and $0 < \phi(X)^T \phi(X) \leq M$, the characteristic of which will be utilized to separate the whole state variable in the system function $h_k(X)$.

2.2 Speed function

Inspired by [27] and [28], an improved speed function is introduced as follows:

$$\mu(t) = \begin{cases} \frac{t_r^3}{(1-\mu_{tr})(t_r-t)^3\mu_0 + \mu_0\mu_{tr}t_r^3}, & t \in [0, t_r] \\ \frac{1}{\mu_0\mu_{tr}}, & t \in [t_r, +\infty) \end{cases} \quad (4)$$

where μ_0 and $\mu_{tr} < 1$ are positive parameters, $t_r > 0$ and $\mu_0\mu_{tr}$ denote finite settling time and ultimate bound of tracking error, respectively.

Lemma 3 [28] The unique properties of speed function in (4) can be described as follows.

- 1) For $t \in [0, t_r]$, $\mu(t)$ is strictly increasing with $\mu(0) = 1/\mu_0$ and $\mu \in [1/\mu_0, 1/\mu_0\mu_{tr}]$ for $t \in [0, +\infty)$.
- 2) At $t = t_r$, $\mu(t)$ reaches its maximum value $1/\mu_0\mu_{tr}$ and remains to be $1/\mu_0\mu_{tr}$ for $t \in [t_r, +\infty)$.
- 3) For $t \in [0, +\infty)$, $\mu^{(i)}(t)$ ($i = 0, 1, 2$) are C^{2-i} and bounded, and $\mu^{-1}(t)\dot{\mu}(t)$ is bounded.

Remark 4 Although some prescribed performance controllers, using exponential performance function $\rho(t) = (\rho_0 - \rho_\infty)e^{-\omega t} + \rho_\infty$ (see [21]–[23]), have been developed to deal with the tracking error, they cannot guarantee that the tracking error enters into a preassigned compact set within a known time. However, the speed function considered in this article can make the convergence of tracking error have the given performance specifications, which is more challenging and difficult.

Fig. 1 Trajectories of $1/\mu$ in different cases.

To achieve the pregiven performance specifications, the following state transformation is defined:

$$s_1 = \tan\left(\frac{\pi}{2}\mu\chi_1\right), \chi_1(0) < \mu_0. \quad (5)$$

From the definition of (5), we have

$$\chi_1 = \frac{2}{\pi\mu} \arctan s_1 \quad (6)$$

and

$$\begin{aligned} \dot{\chi}_1 &= -\frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 + \frac{2}{\pi\mu} \frac{s_1}{1+s_1^2} \\ &= x_2 + h_1(X) - \dot{y}_d \end{aligned} \quad (7)$$

which yields

$$\dot{s}_1 = \Xi x_2 + \Xi h_1(X) - \Xi \dot{y}_d + \Xi \frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 \quad (8)$$

where $\Xi = \pi\mu(1+s_1^2)/2 > 0$.

Remark 5 In contrast to the speed function in [27] and [28], a new parameter μ_0 is introduced to obtain $\mu(0) = \mu_0$ rather than $\mu(0) = 1$, in which the restrictive condition of the initial tracking error $\chi_1(0)$ is relaxed largely. In addition, different from the existing state transformation in [39] and [12], a distinguishing feature, via using (5), is to ensure that the value of function Ξ is always positive, which is very necessary to design a stable filtering error compensation system.

Remark 6 The advantage of using state transformation is to convert the constrained tracking error χ_1 into an equivalent unconstrained signal. It should be noted from (5) that if s_1 is bounded, then $-1/\mu < \chi_1 < 1/\mu$ where the curve of $1/\mu$ is shown in Fig.1. Therefore, by designing the control method to ensure the boundedness of s_1 , the pregiven performance specifications of χ_1 can be realized indirectly.

2.3 Event-triggered mechanism

Inspired by [33], a novel event-triggered mechanism with two thresholds is designed as follows.

$$u(t) = \tau(t_q), t_q \leq t < t_{q+1} \quad (9)$$

$$t_{q+1} = \begin{cases} \inf\{t > t_q \mid |\zeta(t)| \geq \rho_{ax}\}, & \text{if } t < T^\dagger \\ \inf\{t > t_q \mid |\zeta(t)| \geq \rho_{in}\}, & \text{if } t \geq T^\dagger \end{cases} \quad (10)$$

where $\zeta(t) = \tau(t) - u(t)$ denotes the measurement error between the intermediate control $\tau(t)$ and control input $u(t)$, $\rho_{ax}, \rho_{in}, T^\dagger$ are positive design parameters and $\rho_{ax} > \rho_{in}, t_r > T^\dagger, t_q, q \in \mathbb{Z}^+$, denotes controller updating moment, i.e., once (10) is triggered, the actuator will be updated by $\tau(t_{q+1})$. In the period $t \in [t_q, t_{q+1})$, the actuator holds as a constant $\tau(t_q)$. During the initial stage $t \in [0, T^\dagger)$, a relatively large threshold is chosen to deal with large control signal caused by initial tracking error to obtain longer event-triggered intervals. In another condition when tracking error gradually comes to stability, the control signal should be close to zero. Thus, to achieve a better system stabilization performance, a smaller measurement error is designed to obtain a more precise control signal.

Remark 7 Compare with fixed threshold event-triggered strategy in [33], the relative threshold method [35] can effectively reduce the number of triggering events because the output of controller is a time-varying signal during system operation. However, the relative threshold method, in which the control signal is introduced into triggering condition, will complicate the expression of the control algorithm. In order to effectively reduce the number of triggering events and avoid introducing the control signal into triggering condition, a novel event-triggered mechanism with two thresholds is designed in this work, whose superiority will be verified in the following comparative simulations.

3 Control design and stability analysis

3.1 Neural state observer design

Due to unmeasurable state variables and unknown nonlinear functions, the RBF neural networks are utilized to be uncertainty approximators embedded in the observer, and thereby contributing to a neural state observer. Before constructing the neural state observer, the nonstrict-feedback system (1) can be rewritten as

$$\begin{cases} \dot{X} = AX + Ly + \sum_{k=1}^n B_k h_k(X) + Bu \\ y = CX \end{cases} \quad (11)$$

where

$$A = \begin{bmatrix} -l_1 & & & \\ \vdots & I_{n-1} & & \\ -l_n & 0 & \cdots & 0 \end{bmatrix},$$

$$B_k = \underbrace{[0, 0, \dots, 0, 1, 0, \dots, 0]^T}_k, B = [0, \dots, 0, 1]^T, L = [l_1, l_2, \dots, l_n]^T, \text{ and } C = [1, 0, \dots, 0].$$

Via selecting proper L , a strict Hurwitz matrix can be obtained. Therefore, given $Q^T = Q > 0$, there is a positive definite matrix $P^T = P > 0$ satisfying

$$A^T P + PA = -2Q. \quad (12)$$

Construct a neural observer as follows:

$$\dot{\hat{X}} = A\hat{X} + Ly + \sum_{k=1}^n B_k \hat{h}_k(\hat{X} | \theta_k) + Bu \quad (13)$$

where $\hat{X} = [\hat{x}_1, \dots, \hat{x}_n]^T$ are defined to estimate $X = [x_1, \dots, x_n]^T$, and under Lemma 2, the nonlinear functions in (1) can be estimated as $h_k(X | \theta_k) = \theta_k^T \phi_k(X)$ and $\hat{h}_k(\hat{X} | \theta_k) = \theta_k^T \phi_k(\hat{X})$.

Similar to [40]–[42], the variable errors ε_k and δ_k are defined as

$$\begin{cases} \varepsilon_k = h_k(X) - \hat{h}_k(\hat{X} | \theta_k^*) \\ \delta_k = h_k(X) - \hat{h}_k(\hat{X} | \theta_k) \end{cases} \quad (14)$$

where θ_k^* denotes the optimal parameter vector, and we assume that there exist positive constants $\bar{\varepsilon}_k$ and $\bar{\delta}_k$, $k = 1, 2, \dots, n$, such that $|\varepsilon_k| \leq \bar{\varepsilon}_k$ and $|\delta_k| \leq \bar{\delta}_k$.

Denote $\tilde{X} = X - \hat{X} = [\tilde{x}_1, \dots, \tilde{x}_n]^T$ as the observer error. Then from (11) and (13), we can obtain the error dynamics:

$$\begin{aligned} \dot{\tilde{X}} &= A\tilde{X} + \sum_{k=1}^n B_k (h_k(X) - \hat{h}_k(\hat{X} | \theta_k)) \\ &= A\tilde{X} + \delta \end{aligned} \quad (15)$$

where $\delta = [\delta_1, \dots, \delta_n]^T$.

Remark 8 Since only the output y can be used to design the control law, a neural state observer is constructed to estimate unmeasured state vector. Compared with the linear state observer in [43] and [10], the observer (13) uses neural networks to approximate useful information of uncertain function $h_k(X)$ for obtaining better estimation performance

3.2 Event-triggered control design

To avoid the repeated differentiations virtual controllers in the backstepping design, the following tracking errors and command filtered system are defined:

$$\begin{aligned} z_1 &= s_1 \\ z_k &= \hat{x}_k - \lambda_k, \quad k = 2, \dots, n \end{aligned} \quad (16)$$

where λ_k denotes the output of the following command filter with virtual controller α_{k-1}

$$\omega_{k-1} \dot{\lambda}_k + \lambda_k = \alpha_{k-1}, \quad \lambda_k(0) = \alpha_{k-1}(0), \quad k = 2, \dots, n \quad (17)$$

where ω_{k-1} is a positive design parameter.

The following virtual controllers and actual controller are given for $t \in [t_q, t_{q+1})$

$$\begin{aligned} \alpha_1 &= -\frac{c_1 z_1}{\Xi} - \frac{a_{13}}{2} \eta_1 \Xi - a_{11} \eta_1 \Xi - a_{12} \eta_1 \Xi \\ &\quad - \theta_1^T \phi_1(\hat{x}_1) - \frac{2\dot{\mu}}{\pi \mu^2} \arctan s_1 + \dot{y}_d \\ \alpha_2 &= -c_2 z_2 - a_{21} \eta_2 - \frac{a_{23}}{2} \eta_2 - \frac{a_{22}}{2} \eta_2 \\ &\quad - \theta_2^T \phi_2(\hat{X}_2) - l_2 \tilde{x}_1 + \dot{\lambda}_2 - \Xi z_1 \\ \alpha_k &= -c_k z_k - a_{k1} \eta_k - \frac{a_{k3}}{2} \eta_k - \frac{a_{k2}}{2} \eta_k - \theta_k^T \phi_k(\hat{X}_k) \\ &\quad - l_k \tilde{x}_1 + \dot{\lambda}_k - z_{k-1}, \quad k = 3, \dots, n-1 \\ \alpha_n &= -c_n z_n - \frac{a_{n3}}{2} \eta_n - \frac{a_{n2}}{2} \eta_n - \theta_n^T \phi_n(\hat{X}) - l_n \tilde{x}_1 \\ &\quad + \dot{\lambda}_n - z_{n-1} \end{aligned} \quad (18)$$

$$\tau(t) = \alpha_n - \bar{\rho} \tanh\left(\frac{\eta_n \bar{\rho}}{\varpi}\right)$$

$$u(t) = \tau(t_q)$$

where $\bar{\rho} > \rho_{ax} > \rho_{in}$, $\varpi > 0$, $c_k > 0$, $a_{k2} > 0$, $a_{k3} > 0$ and $a_{j1} > 0$, $k = 1, \dots, n$, $j = 1, \dots, n-1$ are design parameters. η_k denotes the compensated tracking error given as

$$\eta_k = z_k - \xi_k, \quad k = 1, 2, \dots, n. \quad (19)$$

where ξ_k is error compensation signal designed in (21). The updating process of parameters can be designed as

$$\begin{aligned} \dot{\theta}_1 &= \pi_1 \Xi \eta_1 \phi_1(\hat{x}_1) - \sigma_1 \theta_1 \\ \dot{\theta}_k &= \pi_k \eta_k \phi_k(\hat{X}_k) - \sigma_k \theta_k, \quad k = 2, \dots, n \end{aligned} \quad (20)$$

where $\hat{X}_k = [\hat{x}_1, \hat{x}_2, \dots, \hat{x}_k]^T$, $k = 2, \dots, n$, $\hat{X}_n = \hat{X}$, $\pi_k > 0$ and $\sigma_k > 0$ are design parameters.

To eliminate the adverse effect of filtering errors $\lambda_k - \alpha_{k-1}$ ($k = 2, \dots, n$), we design the error compensation mechanism as

$$\begin{aligned} \dot{\xi}_1 &= -c_1 \xi_1 + \Xi \xi_2 + \Xi (\lambda_2 - \alpha_1) - \Xi t_1 \text{sign}(\xi_1) \\ \dot{\xi}_2 &= -c_2 \xi_2 - \Xi \xi_1 + \lambda_3 - \alpha_2 + \xi_3 - t_2 \text{sign}(\xi_2) \\ \dot{\xi}_k &= -c_k \xi_k - \xi_{k-1} + \lambda_{k+1} - \alpha_k + \xi_{k+1} - t_k \text{sign}(\xi_k) \\ &\quad (k = 3, \dots, n-1) \\ \dot{\xi}_n &= -c_n \xi_n - \xi_{n-1} - t_n \text{sign}(\xi_n) \end{aligned} \quad (21)$$

with $\xi_k(0) = 0$ ($k = 1, \dots, n$), t_k is a positive design parameter.

Remark 9 Although the dynamic surface technique was employed in [20] to solve the “explosion of complexity” problem for nonstrict-feedback nonlinear systems, the adverse effect of filtering error $\lambda_k - \alpha_{k-1}$ was not addressed, which might degrade control quality. In order to cope with the adverse effect, the error compensation mechanism in (21) is developed at each step of the control strategy.

3.3 Stability analysis

In this section, the specifics of developed event-triggered control strategy are presented according to the backstepping technique, where the n recursive steps are involved.

Step 1: Based on the compensated tracking errors (19), the derivative of η_1 is given as

$$\begin{aligned}\dot{\eta}_1 &= \dot{z}_1 - \dot{\xi}_1 \\ &= \Xi \tilde{x}_2 + \Xi (z_2 + \lambda_2) + \Xi \left(\theta_1^{*T} \phi_1(\hat{X}) + \varepsilon_1 \right. \\ &\quad \left. - \dot{y}_d + \frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 \right) - \dot{\xi}_1 \\ &= \Xi \tilde{x}_2 + \Xi (z_2 + \lambda_2) + \Xi \varepsilon_1 - \dot{\xi}_1 \\ &\quad + \Xi \left(\theta_1^{*T} \phi_1(\hat{X}) - \theta_1^{*T} \phi_1(\hat{x}_1) \right) + \Xi \theta_1^T \phi_1(\hat{x}_1) \\ &\quad + \Xi \tilde{\theta}_1^T \phi_1(\hat{x}_1) + \Xi \left(\frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 - \dot{y}_d \right)\end{aligned}\quad (22)$$

where $\tilde{\theta}_1 = \theta_1^* - \theta_1$. Constructing the Lyapunov function

$$V_1 = V_{\tilde{x}} + \frac{1}{2} \eta_1^2 + \frac{1}{2\pi_1} \tilde{\theta}_1^2 \quad (23)$$

where $V_{\tilde{x}} = \tilde{X}^T P \tilde{X} / 2$. Its time derivative is obtained as

$$\begin{aligned}\dot{V}_1 &= \dot{V}_{\tilde{x}} + \eta_1 \dot{\eta}_1 - \frac{1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1 \\ &= -\tilde{X}^T Q \tilde{X} + \tilde{X}^T P \delta + \eta_1 (\Xi \tilde{x}_2 + \Xi \eta_2 + \Xi \alpha_1 \\ &\quad + \Xi \left(\theta_1^{*T} \phi_1(\hat{X}) - \theta_1^{*T} \phi_1(\hat{x}_1) \right) + \Xi \theta_1^T \phi_1(\hat{x}_1) \\ &\quad + \Xi \tilde{\theta}_1^T \phi_1(\hat{x}_1) + \Xi \varepsilon_1 + \Xi \left(\frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 - \dot{y}_d \right) \\ &\quad + c_1 \xi_1 + \Xi \iota_1 \text{sign}(\xi_1)) - \frac{1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1\end{aligned}\quad (24)$$

By Young's inequality, and applying the property of RBF, that is $0 < \phi_1(\cdot)^T \phi_1(\cdot) \leq M_1$, one has

$$\eta_1 \Xi \left(\theta_1^{*T} \phi_1(\hat{X}) - \theta_1^{*T} \phi_1(\hat{x}_1) \right) \leq a_{11} \eta_1^2 \Xi^2 + \frac{\|\theta_1^*\|^2 M_1}{a_{11}} \quad (25)$$

$$\eta_1 \Xi \varepsilon_1 + \eta_1 \Xi \iota_1 \text{sign}(\xi_1) \leq a_{12} \eta_1^2 \Xi^2 + \frac{\bar{\varepsilon}_1^2}{2a_{12}} + \frac{\iota_1^2}{2a_{12}} \quad (26)$$

$$\eta_1 \Xi \tilde{x}_2 \leq \frac{a_{13}}{2} \eta_1^2 \Xi^2 + \frac{\|\tilde{X}\|^2}{2a_{13}} \quad (27)$$

$$\tilde{X}^T P \delta \leq \frac{a_{14}}{2} \|P\delta\|^2 + \frac{\|\tilde{X}\|^2}{2a_{14}} \quad (28)$$

Substituting (25)-(28) into (24), yields

$$\begin{aligned}\dot{V}_1 &\leq -\tilde{X}^T \left(\lambda_{\min}(Q) - \frac{1}{2a_{13}} - \frac{1}{2a_{14}} \right) \tilde{X} + \Xi \eta_1 \eta_2 \\ &\quad + \Xi \eta_1 \tilde{\theta}_1^T \phi_1(\hat{x}_1) - \frac{1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1 + \eta_1 \Xi (\alpha_1 \\ &\quad + \frac{a_{13}}{2} \eta_1 \Xi + a_{11} \eta_1 \Xi + a_{12} \eta_1 \Xi + \theta_1^T \phi_1(\hat{x}_1) \\ &\quad + \frac{2\dot{\mu}}{\pi\mu^2} \arctan s_1 - \dot{y}_d + \frac{c_1 \xi_1}{\Xi}) + \frac{a_{14}}{2} \|P\delta\|^2 \\ &\quad + \frac{\|\theta_1^*\|^2 M_1}{a_{11}} + \frac{\bar{\varepsilon}_1^2}{2a_{12}} + \frac{\iota_1^2}{2a_{12}}\end{aligned}\quad (29)$$

Then, substituting α_1 and $\dot{\theta}_1$ into (29), one has

$$\dot{V}_1 \leq -\mu_1 \tilde{X}^T \tilde{X} - c_1 \eta_1^2 + \Xi \eta_1 \eta_2 + \frac{\sigma_1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1 + \Lambda_1 \quad (30)$$

where $\Lambda_1 = a_{14} \|P\delta\|^2 / 2 + \|\theta_1^*\|^2 M_1 / a_{11} + \bar{\varepsilon}_1^2 / (2a_{12}) + \iota_1^2 / (2a_{12})$ and $\mu_1 = \lambda_{\min}(Q) - 1/(2a_{13}) - 1/(2a_{14}) > 0$.

Step 2: The derivative of η_2 is

$$\begin{aligned}\dot{\eta}_2 &= \dot{z}_2 - \dot{\xi}_2 \\ &= \hat{x}_3 + \hat{h}_2(\hat{X} | \theta_2) + l_2 \tilde{x}_1 - \dot{\lambda}_2 - \dot{\xi}_2 \\ &= z_3 + \lambda_3 + \theta_2^{*T} \phi_2(\hat{X}) - \tilde{\theta}_2^T \phi_2(\hat{X}) + l_2 \tilde{x}_1 - \dot{\lambda}_2 \\ &\quad - \dot{\xi}_2 - \theta_2^{*T} \phi_2(\hat{X}_2) + \theta_2^T \phi_2(\hat{X}_2) + \tilde{\theta}_2^T \phi_2(\hat{X}_2)\end{aligned}\quad (31)$$

where $\tilde{\theta}_2 = \theta_2^* - \theta_2$. The Lyapunov function is constructed as

$$V_2 = V_1 + \frac{1}{2} \eta_2^2 + \frac{1}{2\pi_2} \tilde{\theta}_2^2 \quad (32)$$

Then we have

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + \eta_2 \dot{\eta}_2 - \frac{1}{\pi_2} \tilde{\theta}_2^T \dot{\theta}_2 \\ &= \dot{V}_1 - \frac{1}{\pi_2} \tilde{\theta}_2^T \dot{\theta}_2 + \eta_2 \left(\eta_3 + \alpha_2 + \theta_2^{*T} \phi_2(\hat{X}) \right. \\ &\quad \left. - \tilde{\theta}_2^T \phi_2(\hat{X}) - \theta_2^{*T} \phi_2(\hat{X}_2) + \theta_2^T \phi_2(\hat{X}_2) \right. \\ &\quad \left. + \tilde{\theta}_2^T \phi_2(\hat{X}_2) + l_2 \tilde{x}_1 - \dot{\lambda}_2 + c_2 \xi_2 + \Xi \xi_1 \right. \\ &\quad \left. + l_2 \text{sign}(\xi_2) \right).\end{aligned}\quad (33)$$

Similar to step 1, we can obtain

$$\eta_2 \left(\theta_2^{*T} \phi_2(\hat{X}) - \theta_2^{*T} \phi_2(\hat{X}_2) \right) \leq a_{21} \eta_2^2 + \frac{\|\theta_2^*\|^2 M_2}{a_{21}} \quad (34)$$

$$\eta_2 l_2 \text{sign}(\xi_2) \leq \frac{a_{22}}{2} \eta_2^2 + \frac{\iota_2^2}{2a_{22}} \quad (35)$$

$$-\eta_2 \tilde{\theta}_2^T \phi_2(\hat{X}) \leq \frac{a_{23}}{2} \eta_2^2 + \frac{\tilde{\theta}_2^T \tilde{\theta}_2 M_2}{2a_{23}} \quad (36)$$

Substituting (34)–(36) into (33), yields

$$\begin{aligned} \dot{V}_2 \leq & -\mu_1 \tilde{X}^T \tilde{X} - c_1 \eta_1^2 + \frac{\sigma_1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1 + \Lambda_1 + \eta_2 \eta_3 \\ & + \eta_2 \left(\alpha_2 + a_{21} \eta_2 + \frac{a_{23}}{2} \eta_2 + \frac{a_{22}}{2} \eta_2 \right. \\ & \left. + \theta_2^T \phi_2(\hat{X}_2) + l_2 \tilde{x}_1 - \dot{\lambda}_2 + c_2 \xi_2 + \Xi_{z1} \right) \\ & + \eta_2 \tilde{\theta}_2^T \phi_2(\hat{X}_2) - \frac{1}{\pi_2} \tilde{\theta}_2^T \dot{\theta}_2 + \frac{\tilde{\theta}_2^T \tilde{\theta}_2 M_2}{2a_{23}} \\ & + \frac{\|\theta_2^*\|^2 M_2}{a_{21}} + \frac{l_2^2}{2a_{22}} \end{aligned} \quad (37)$$

Then, substituting α_2 and $\dot{\theta}_2$ into (37), one has

$$\begin{aligned} \dot{V}_2 \leq & -\mu_1 \tilde{X}^T \tilde{X} - c_1 \eta_1^2 - c_2 \eta_2^2 + \eta_2 \eta_3 \\ & + \frac{\sigma_1}{\pi_1} \tilde{\theta}_1^T \dot{\theta}_1 + \frac{\sigma_2}{\pi_2} \tilde{\theta}_2^T \dot{\theta}_2 + \frac{\tilde{\theta}_2^T \tilde{\theta}_2 M_2}{2a_{23}} + \Lambda_2 \end{aligned} \quad (38)$$

where $\Lambda_2 = \Lambda_1 + \|\theta_2^*\|^2 M_2 / a_{21} + l_2^2 / (2a_{22})$.

Step k ($k = 3, \dots, n-1$): The derivative of η_k is

$$\begin{aligned} \dot{\eta}_k &= \dot{z}_k - \dot{\xi}_k \\ &= \hat{x}_{k+1} + \hat{h}_k(\hat{X} | \theta_k) + l_k \tilde{x}_1 - \dot{\lambda}_k - \dot{\xi}_k \\ &= z_{k+1} + \lambda_{k+1} + \theta_k^{*T} \phi_k(\hat{X}) - \tilde{\theta}_k^T \phi_k(\hat{X}) + l_k \tilde{x}_1 \\ &\quad - \dot{\lambda}_k - \dot{\xi}_k - \theta_k^{*T} \phi_k(\hat{X}_k) + \theta_k^T \phi_k(\hat{X}_k) \\ &\quad + \tilde{\theta}_k^T \phi_k(\hat{X}_k) \end{aligned} \quad (39)$$

where $\tilde{\theta}_k = \theta_k^* - \theta_k$. The Lyapunov function is constructed as

$$V_k = V_{k-1} + \frac{1}{2} \eta_k^2 + \frac{1}{2\pi_k} \tilde{\theta}_k^2 \quad (40)$$

Then we have

$$\begin{aligned} \dot{V}_k &= \dot{V}_{k-1} + \eta_k \dot{\eta}_k - \frac{1}{\pi_k} \tilde{\theta}_k^T \dot{\theta}_k \\ &= \dot{V}_{k-1} - \frac{1}{\pi_k} \tilde{\theta}_k^T \dot{\theta}_k \\ &\quad + \eta_k \left(\eta_{k+1} + \alpha_k + \theta_k^{*T} \phi_k(\hat{X}) - \tilde{\theta}_k^T \phi_k(\hat{X}) \right. \\ &\quad \left. - \theta_k^{*T} \phi_k(\hat{X}_k) + \theta_k^T \phi_k(\hat{X}_k) + \tilde{\theta}_k^T \phi_k(\hat{X}_k) \right. \\ &\quad \left. + l_k \tilde{x}_1 - \dot{\lambda}_k + c_k \xi_k + \xi_{k-1} + l_k \text{sign}(\xi_k) \right). \end{aligned} \quad (41)$$

Similar to step 2, we can obtain

$$\eta_k \left(\theta_k^{*T} \phi_k(\hat{X}) - \theta_k^{*T} \phi_k(\hat{X}_k) \right) \leq a_{k1} \eta_k^2 + \frac{\|\theta_k^*\|^2 M_k}{a_{k1}} \quad (42)$$

$$\eta_k l_k \text{sign}(\xi_k) \leq \frac{a_{k2}}{2} \eta_k^2 + \frac{l_k^2}{2a_{k2}} \quad (43)$$

$$-\eta_k \tilde{\theta}_k^T \phi_k(\hat{X}) \leq \frac{a_{k3}}{2} \eta_k^2 + \frac{\tilde{\theta}_k^T \tilde{\theta}_k M_k}{2a_{k3}} \quad (44)$$

Substituting (42)–(44) into (41), yields

$$\begin{aligned} \dot{V}_k \leq & \dot{V}_{k-1} + \eta_k \eta_{k+1} + \eta_k \left(\alpha_k + a_{k1} \eta_k + \frac{a_{k3}}{2} \eta_k \right. \\ & \left. + \frac{a_{k2}}{2} \eta_k + \theta_k^T \phi_k(\hat{X}_k) + l_k \tilde{x}_1 - \dot{\lambda}_k + c_k \xi_k \right. \\ & \left. + \xi_{k-1} \right) + \eta_k \tilde{\theta}_k^T \phi_k(\hat{X}_k) - \frac{1}{\pi_k} \tilde{\theta}_k^T \dot{\theta}_k \\ & + \frac{\tilde{\theta}_k^T \tilde{\theta}_k M_k}{2a_{k3}} + \frac{\|\theta_k^*\|^2 M_k}{a_{k1}} + \frac{l_k^2}{2a_{k2}} \end{aligned} \quad (45)$$

Then, substituting α_k and $\dot{\theta}_k$ into (45), one has

$$\begin{aligned} \dot{V}_k \leq & -\mu_1 \tilde{X}^T \tilde{X} - \sum_{i=1}^k c_i \eta_i^2 + \eta_k \eta_{k+1} + \sum_{i=1}^k \frac{\sigma_i}{\pi_i} \tilde{\theta}_i^T \dot{\theta}_i \\ & + \sum_{i=2}^k \frac{\tilde{\theta}_i^T \tilde{\theta}_i M_i}{2a_{i3}} + \Lambda_k \end{aligned} \quad (46)$$

where $\Lambda_k = \Lambda_{k-1} + \|\theta_k^*\|^2 M_k / a_{k1} + l_k^2 / (2a_{k2})$.

Remark 10 It can be noticed that the function $\hat{h}_k(\hat{X} | \theta_k)$ in the neural observer (13) contains the whole state estimate $\hat{X} = [\hat{x}_1, \dots, \hat{x}_n]^T$. To ensure that only partial state estimate $\hat{X}_k = [\hat{x}_1, \dots, \hat{x}_k]^T$ is included in the virtual controller α_k , we employ Young's inequality and the structural property of RBF to deal with the whole variable $\hat{X}$, which solves the problem of algebraic loop. Compared with [15]–[16] and [12], the method in this article neither needs the restrictive condition that the unknown function satisfies monotonically increasing property, nor needs to introduce additional low-pass filter.

Step n : The actual controller will be given in this final step, the derivative of η_n is

$$\begin{aligned} \dot{\eta}_n &= \dot{z}_n - \dot{\xi}_n \\ &= u + \hat{h}_n(\hat{X} | \theta_n) + l_n \tilde{x}_1 - \dot{\lambda}_n - \dot{\xi}_n \\ &= u + \theta_n^T \phi_n(\hat{X}) - \tilde{\theta}_n^T \phi_n(\hat{X}) + \tilde{\theta}_n^T \phi_n(\hat{X}) \\ &\quad + l_n \tilde{x}_1 - \dot{\lambda}_n - \dot{\xi}_n. \end{aligned} \quad (47)$$

Choose the Lyapunov function

$$V_n = V_{n-1} + \frac{1}{2} \eta_n^2 + \frac{1}{2\pi_n} \tilde{\theta}_n^2. \quad (48)$$

Then we have

$$\begin{aligned} \dot{V}_n &= \dot{V}_{n-1} + \eta_n \dot{\eta}_n - \frac{1}{\pi_n} \tilde{\theta}_n^T \dot{\theta}_n \\ &= \dot{V}_{n-1} - \frac{1}{\pi_n} \tilde{\theta}_n^T \dot{\theta}_n + \eta_n \tilde{\theta}_n^T \phi_n(\hat{X}) \\ &\quad + \eta_n \left(u + \theta_n^T \phi_n(\hat{X}) - \tilde{\theta}_n^T \phi_n(\hat{X}) + l_n \tilde{x}_1 \right. \\ &\quad \left. - \dot{\lambda}_n + c_n \xi_n + \xi_{n-1} + l_n \text{sign}(\xi_n) \right). \end{aligned} \quad (49)$$

Applying Young's inequality yields

$$\eta_n \iota_n \text{sign}(\xi_n) \leq \frac{a_{n2}}{2} \eta_n^2 + \frac{\iota_n^2}{2a_{n2}} \quad (50)$$

$$-\eta_n \tilde{\theta}_n^T \phi_n(\hat{X}) \leq \frac{a_{n3}}{2} \eta_n^2 + \frac{\tilde{\theta}_n^T \tilde{\theta}_n M_n}{2a_{n3}}. \quad (51)$$

Substituting (50)–(51) into (49), yields

$$\begin{aligned} \dot{V}_n &\leq \dot{V}_{n-1} + \eta_n \left(u + \frac{a_{n3}}{2} \eta_n + \frac{a_{n2}}{2} \eta_n + \theta_n^T \phi_n(\hat{X}) \right. \\ &\quad \left. + l_n \tilde{x}_1 - \dot{\lambda}_n + c_n \xi_n + \xi_{n-1} \right) + \eta_n \tilde{\theta}_n^T \phi_n(\hat{X}) \\ &\quad - \frac{1}{\pi_n} \tilde{\theta}_n^T \dot{\theta}_n + \frac{\tilde{\theta}_n^T \tilde{\theta}_n M_n}{2a_{n3}} + \frac{\iota_n^2}{2a_{n2}}. \end{aligned} \quad (52)$$

In the interval $t \in [t_q, t_{q+1})$, from (10), we know that

$$|\tau(t) - u(t)| < \rho_{ax}. \quad (53)$$

So, there is a time-varying parameter $|\kappa(t)| \leq 1$ satisfying

$$u(t) = \tau(t) - \kappa(t) \rho_{ax}. \quad (54)$$

By substituting $\tau(t)$ and (54) into (52), we have

$$\begin{aligned} \dot{V}_n &\leq \dot{V}_{n-1} + \eta_n \left(\alpha_n - \bar{\rho} \tanh\left(\frac{\eta_n \bar{\rho}}{\varpi}\right) - \kappa(t) \rho_{ax} \right. \\ &\quad \left. + \frac{a_{n3}}{2} \eta_n + \frac{a_{n2}}{2} \eta_n + \theta_n^T \phi_n(\hat{X}) + l_n \tilde{x}_1 \right. \\ &\quad \left. - \dot{\lambda}_n + c_n \xi_n + \xi_{n-1} \right) + \eta_n \tilde{\theta}_n^T \phi_n(\hat{X}) \\ &\quad - \frac{1}{\pi_n} \tilde{\theta}_n^T \dot{\theta}_n + \frac{\tilde{\theta}_n^T \tilde{\theta}_n M_n}{2a_{n3}} + \frac{\iota_n^2}{2a_{n2}}. \end{aligned} \quad (55)$$

Substitute α_n and $\dot{\theta}_n$ into (55), yields

$$\begin{aligned} \dot{V}_n &\leq -\mu_1 \tilde{X}^T \tilde{X} - \sum_{k=1}^n c_k \eta_k^2 + \sum_{k=1}^n \frac{\sigma_k}{\pi_k} \tilde{\theta}_k^T \theta_k \\ &\quad + \sum_{k=2}^n \frac{\tilde{\theta}_k^T \tilde{\theta}_k M_k}{2a_{k3}} + \Lambda_n + \eta_n \left(-\bar{\rho} \tanh\left(\frac{\eta_n \bar{\rho}}{\varpi}\right) \right. \\ &\quad \left. - \kappa(t) \rho_{ax} \right) \end{aligned} \quad (56)$$

where $\Lambda_n = \Lambda_{n-1} + \iota_n^2 / (2a_{n2})$. From $\tilde{\theta}_k = \theta_k^* - \theta_k$, one has

$$\tilde{\theta}_k^T \theta_k \leq \frac{1}{2} \theta_k^{*T} \theta_k^* - \frac{1}{2} \tilde{\theta}_k^T \tilde{\theta}_k \quad (57)$$

then

$$\sum_{k=1}^n \frac{\sigma_k}{\pi_k} \tilde{\theta}_k^T \theta_k \leq -\sum_{k=1}^n \frac{\sigma_k}{2\pi_k} \tilde{\theta}_k^T \tilde{\theta}_k + \sum_{k=1}^n \frac{\sigma_k}{2\pi_k} \theta_k^{*T} \theta_k^* \quad (58)$$

Based on Lemma 1, $\bar{\rho} > \rho_{ax}$ and $|\kappa(t)| \leq 1$, from (56) and (58), we have

$$\begin{aligned} \dot{V}_n &\leq -\mu_1 \tilde{X}^T \tilde{X} - \sum_{k=1}^n c_k \eta_k^2 + \sum_{k=1}^n \frac{\sigma_k}{\pi_k} \tilde{\theta}_k^T \theta_k \\ &\quad + \sum_{k=2}^n \frac{\tilde{\theta}_k^T \tilde{\theta}_k M_k}{2a_{k3}} + \Lambda_n - \eta_n \bar{\rho} \tanh\left(\frac{\eta_n \bar{\rho}}{\varpi}\right) \\ &\quad + |\eta_n \bar{\rho}| \\ &\leq -\mu_1 \tilde{X}^T \tilde{X} - \sum_{k=1}^n c_k \eta_k^2 - \left(\frac{\sigma_1}{2\pi_1} \tilde{\theta}_1^T \tilde{\theta}_1 + \right. \\ &\quad \left. \sum_{k=2}^n \left(\frac{\sigma_k}{2\pi_k} - \frac{M_k}{2a_{k3}} \right) \tilde{\theta}_k^T \tilde{\theta}_k \right) + \Lambda'_n \end{aligned} \quad (59)$$

where $\Lambda'_n = \Lambda_n + \sum_{k=1}^n \sigma_k \theta_k^{*T} \theta_k^* / 2\pi_k + 0.2785\varpi$.

According to the above analysis, the main result of this article is stated as follows.

Theorem 1 For the nonstrict-feedback uncertain nonlinear systems (1) with Assumption 1, design the neural state observer (13), the command filtered system (17), error compensation system (21), the virtual controllers and actual controller (18), the adaptive updating laws (20), then the proposed event-triggered control strategy can guarantee that the tracking error converges to a prescribed small region near zero within preset finite time t_r at predesigned converging mode during the period $t \in [0, t_r)$ and all the signals $x_k, \hat{x}_k, z_k, \eta_k, \xi_k, \alpha_k, k = 1, \dots, n, \tau(t)$ and $u(t)$ are bounded. In addition, $\forall q \in \mathbb{Z}^+$, there is a positive instant $t^* > 0$ satisfying $\{t_{q+1} - t_q\} \geq t^*$.

Proof: To prove the stability of the error compensation system (21), we choose the Lyapunov function as $V_\xi = \sum_{k=1}^n \xi_k^2 / 2$. Then, the derivative of V_ξ is obtained as

$$\begin{aligned} \dot{V}_\xi &= -c_1 \xi_1^2 + \Xi \xi_1 \xi_2 + \Xi (\lambda_2 - \alpha_1) \xi_1 - \Xi \iota_1 |\xi_1| \\ &\quad - c_2 \xi_2^2 - \Xi \xi_1 \xi_2 + (\lambda_3 - \alpha_2) \xi_2 + \xi_2 \xi_3 \\ &\quad - \iota_2 |\xi_2| + \dots - c_k \xi_k^2 - \xi_{k-1} \xi_k \\ &\quad + (\lambda_{k+1} - \alpha_k) \xi_k + \xi_k \xi_{k+1} - \iota_k |\xi_k| \\ &\quad + \dots - c_n \xi_n^2 - \xi_{n-1} \xi_n - \iota_n |\xi_n| \\ &= -\sum_{k=1}^n c_k \xi_k^2 - \Xi (\iota_1 |\xi_1| - (\lambda_2 - \alpha_1) \xi_1) \\ &\quad - \sum_{k=2}^{n-1} (\iota_k |\xi_k| - (\lambda_{k+1} - \alpha_k) \xi_k) - \iota_n |\xi_n| \end{aligned} \quad (60)$$

Similar to [44] and [45], we can get that $|(\lambda_{k+1} - \alpha_k)| \leq \beta_k, k = 1, \dots, n-1$, can be achieved with the positive constant β_k . Since $\Xi > 0$, via choosing suitable parameter $\iota_k >$

β_k , one has

$$\dot{V}_\xi \leq -\sum_{k=1}^n c_k \xi_k^2 \quad (61)$$

To analysis the stability of the closed-loop system, we construct the whole Lyapunov function as

$$V = V_n + V_\xi. \quad (62)$$

The derivative of V is obtained as

$$\begin{aligned} \dot{V} \leq & -\frac{2\mu_1}{\lambda_{\max}(P)} \frac{\tilde{X}^T P \tilde{X}}{2} - 2 \sum_{k=1}^n c_k \frac{\eta_k^2}{2} \\ & - \left(\sigma_1 \frac{\tilde{\theta}_1^T \tilde{\theta}_1}{2\pi_1} + \sum_{k=2}^n \left(\sigma_k - \frac{2\pi_k M_k}{2a_{k3}} \right) \frac{\tilde{\theta}_k^T \tilde{\theta}_k}{2\pi_k} \right) \\ & - 2 \sum_{k=1}^n c_k \frac{\xi_k^2}{2} + \Lambda'_n \\ \leq & -\Theta V + \Lambda'_n \end{aligned} \quad (63)$$

where $\Theta = \min \{2\mu_1/\lambda_{\max}(P), 2c_k, \sigma_1, \sigma_k - 2\pi_k M_k/(2a_{k3})\}$.

Furthermore, select the design parameters σ_k, π_k, a_{k3} so that $\sigma_k - 2\pi_k M_k/(2a_{k3}) > 0$. Consequently, from (63), we have

$$V(t) \leq V(0)e^{-\Theta t} + \frac{\Lambda'_n}{\Theta}. \quad (64)$$

Then it can be obtained that $\eta_k, \tilde{\theta}_k, \xi_k$ and $\theta_k, k = 1, \dots, n$ are bounded. From $z_k = \eta_k + \xi_k$, z_k is bounded. Next, x_1 and $\hat{x}_1$ are bounded as y_d is bounded, which implies that α_1 and λ_2 are bounded. Similarly, we can prove $x_k, \hat{x}_k, \alpha_k, \tau(t)$ and $u(t)$ are also bounded. Therefore, all the signals inside the closed-loop system are bounded.

Furthermore, since $z_1 = s_1$ is bounded, we obtain

$$\begin{aligned} |\chi_1| & < \left| \frac{1}{\mu} \right| \\ & = \begin{cases} \left| \frac{(1-\mu_r)(t_r-t)^3 \mu_0 + \mu_0 \mu_r t_r^3}{t_r^3} \right|, & t \in [0, t_r) \\ \mu_0 \mu_r, & t \in [t_r, +\infty) \end{cases} \end{aligned} \quad (65)$$

which implies that the error $|\chi_1|$ reduces to $\mu_0 \mu_r$ within a pregiven time t_r at predesigned converging mode governed by $(1-\mu_r)(t_r-t)^3 \mu_0/t_r^3$.

Next, we prove that there exists $t^* > 0$ such that $\{t_{q+1} - t_q\} \geq t^*, \forall q \in \mathbb{Z}^+$. Based on $\varsigma(t) = \tau(t) - u(t), \forall t \in [t_q, t_{q+1})$, one has

$$\begin{aligned} \frac{d}{dt} |\varsigma(t)| & = \frac{d}{dt} \sqrt{\varsigma(t) \cdot \varsigma(t)} \\ & = \text{sign}(\varsigma(t)) \dot{\varsigma}(t) \\ & \leq |\dot{\tau}(t)|. \end{aligned} \quad (66)$$

From (18), we can demonstrate that $\tau(t)$ is differentiable and its time derivative $\dot{\tau}(t)$ is a function with all bounded signals, which implies that there is a positive constant $\gamma > 0$

satisfying $|\dot{\tau}(t)| \leq \gamma$. In addition, $\varsigma(t_q) = 0$ and $\lim_{t \rightarrow t_{q+1}} \varsigma(t) \geq \rho_{in}$, so the lower bound of event-triggered time intervals t^* must satisfy $t^* \geq \rho_{in}/\gamma > 0$. Therefore, the Zeno-behaviour is ruled out.

Remark 11 It can be demonstrated from (65) that in the interval $t \in [t_q, t_{q+1})$, if the value of μ_0 determined by the initial tracking error $\chi_1(0)$ does not change, then the converging rate of $|\chi_1|$ is affected not only by μ_r but also by t_r . A faster tracking process can be achieved by decreasing μ_r or shortening preset time t_r , which will be shown in the later simulation comparison experiment.

Remark 12 The developed event-triggered output feedback control strategy can obtain given performance specifications for the tracking error. Such solution, very useful in practical engineering, has never been proposed for the uncertain nonstrict-feedback systems, as described in (1).

4 Simulation Examples

This section is to demonstrate the effectiveness and superiority of the developed control strategy by two examples.

Example 1: Consider the nonstrict-feedback nonlinear system as follows

$$\begin{cases} \dot{x}_1 = x_2 + h_1(X) \\ \dot{x}_2 = u + h_2(X) \\ y = x_1 \end{cases} \quad (67)$$

where $h_1(X) = x_2 e^{-0.5x_1}, h_2(X) = x_1 \sin(x_2^2)$. The initial states are given as $x_1(0) = 2, x_2(0) = 0, \hat{x}_1(0) = 1.5$ and $\hat{x}_1(0) = -2$. The desired reference signal is $y_d = \sin(t)$.

Construct the following neural state observer

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 + l_1(y - \hat{x}_1) + \theta_1^T \phi_1(\hat{X}) \\ \dot{\hat{x}}_2 = u + l_2(y - \hat{x}_1) + \theta_2^T \phi_2(\hat{X}) \end{cases} \quad (68)$$

where the observer gain vector is designed as $L = [l_1, l_2] = [29.9643, 113.4592]$. $\theta_1^T \phi_1(\hat{X})$ and $\theta_2^T \phi_2(\hat{X})$ contain 125 nodes and 75 nodes respectively. For each of two neural networks, centers are spaced evenly in $[-1, 2] \times [-2, 1.5]$ and widths are equal to 3.85. The parameter update laws are given as

$$\begin{aligned} \dot{\theta}_1 & = \pi_1 \Xi \eta_1 \phi_1(\hat{x}_1) - \sigma_1 \theta_1 \\ \dot{\theta}_2 & = \pi_2 \eta_2 \phi_2(\hat{X}) - \sigma_2 \theta_2 \end{aligned} \quad (69)$$

with $\theta_1(0) = 0_{125 \times 1}$ and $\theta_2(0) = 0_{75 \times 1}$.

Then, we design virtual controllers, actual controller and event-triggered mechanism as

$$\begin{aligned}\alpha_1 &= -\frac{c_1 z_1}{\Xi} - \frac{a_{13}}{2} \eta_1 \Xi - a_{11} \eta_1 \Xi - a_{12} \eta_1 \Xi \\ &\quad - \theta_1^T \phi_1(\hat{x}_1) - \frac{2\dot{\mu}}{\pi \mu^2} \arctan s_1 + \dot{y}_d \\ \alpha_2 &= -c_2 z_2 - \frac{a_{23}}{2} \eta_2 - \frac{a_{22}}{2} \eta_2 - \theta_2^T \phi_2(\hat{X}) \\ &\quad - l_2 \tilde{x}_1 + \dot{\lambda}_2 - \Xi z_1\end{aligned}\quad (70)$$

$$\tau(t) = \alpha_2 - \bar{\rho} \tanh\left(\frac{\eta_2 \bar{\rho}}{\bar{\omega}}\right)$$

$$u(t) = \tau(t_q)$$

$$t_{q+1} = \begin{cases} \inf\{t > t_q \mid |\zeta(t)| \geq \rho_{ax}\}, & \text{if } t < T^\dagger \\ \inf\{t > t_q \mid |\zeta(t)| \geq \rho_{in}\}, & \text{if } t \geq T^\dagger \end{cases}$$

where the command filter system is given as

$$\omega_1 \dot{\lambda}_2 + \lambda_2 = \alpha_1, \quad \lambda_2(0) = \alpha_1(0) \quad (71)$$

and the error compensation mechanism is constructed as

$$\begin{aligned}\dot{\xi}_1 &= -c_1 \xi_1 + \Xi \xi_2 + \Xi (\lambda_2 - \alpha_1) - \Xi t_1 \text{sign}(\xi_1) \\ \dot{\xi}_2 &= -c_2 \xi_2 - \Xi \xi_1 - t_2 \text{sign}(\xi_2)\end{aligned}\quad (72)$$

with $\xi_k(0) = 0$ ($k = 1, 2$).

In the simulation, choosing the design parameters as $c_1=0.1$, $c_2=5$, $\bar{\rho}=9$, $\bar{\omega}=15$, $\omega_1=0.01$, $t_1=t_2=0.1$, $t_r=5$, $\mu_{tr}=0.05$, $\mu_0=2.5$, $T^\dagger=1$, $\rho_{ax}=8$, $\rho_{in}=0.2$, $\pi_1=\pi_2=0.01$, $\sigma_1=\sigma_2=1$, $a_{11}=a_{12}=0.025$, $a_{13}=0.1$, $a_{23}=0.9$, $a_{22}=0.1$.

To show the effectiveness of event-triggered mechanism, comparative simulations between the fixed threshold approach, relative threshold strategy and the presented method are carried out. The fixed threshold approach can be obtained from [33] and it is given as follows:

$$\begin{aligned}\tau(t) &= \alpha_2 - \bar{\rho} \tanh\left(\frac{\eta_2 \bar{\rho}}{\bar{\omega}}\right) \\ u(t) &= \tau(t_q)\end{aligned}\quad (73)$$

$$t_{q+1} = \inf\{t > t_q \mid |\zeta(t)| \geq \rho_{fix}\}$$

where $\bar{\rho} = 9$ and the value of ρ_{fix} is selected as 0.2, 4.2 and 8, respectively, for comparative simulations.

The relative threshold strategy from [34] is given as follows:

$$\begin{aligned}\tau_{rel}(t) &= -(1 + \sigma_{rel}) \left(\alpha_2 \tanh\left(\frac{\eta_2 \alpha_2}{\bar{\omega}_{rel}}\right) \right. \\ &\quad \left. + \bar{\rho}_{rel} \tanh\left(\frac{\eta_2 \bar{\rho}_{rel}}{\bar{\omega}_{rel}}\right) \right)\end{aligned}\quad (74)$$

$$u_{rel}(t) = \tau_{rel}(t_q)$$

$$t_{q+1} = \inf\{t > t_q \mid |\zeta(t)| \geq \sigma_{rel} |u_{rel}(t)| + \rho_{rel}\}$$

where $\bar{\rho}_{rel} = 0.09$, $\sigma_{rel} = 0.4$, $\bar{\omega}_{rel} = 5$ and $\rho_{rel} = 0.05$.

Fig. 2 Trajectories of y_d and x_1 in Example 1.

Fig. 3 Trajectories of x_1 and $\hat{x}_1$ in Example 1.

Figs. 2–8 describe simulation results, where Fig. 5 shows that the tracking error χ_1 converges to a small region around zero within a preset time $t_r=5$ at predesigned decay rate. It also points out that the proposed method can obtain superior tracking performance according to faster response and smaller oscillation. For the proposed method, Fig. 3 and Fig. 4 show the system state and estimation of them, the control signal is shown in Fig. 6 and the trajectories of the norm of the adaptive parameters $\|\theta_1\|$ and $\|\theta_2\|$ are shown in Fig. 7 and Fig. 8.

Furthermore, performance comparisons of the presented method, the fixed threshold approach and relative threshold strategy are summarized in Table I. The integrated time absolute and integrated absolute error in [46], labelled as ITAE and IAE, are employed to evaluate dynamic performance and stable precision of tracking controllers, respectively, where $\text{ITAE} = \int_0^{20} v |\chi_1(v)| dv$ and $\text{IAE} = \int_0^{20} |\chi_1(v)| dv$. Table I demonstrates that the presented method is superior to the other two event-triggered mechanisms since it has the lower ITAE and IAE while requiring less triggering numbers.

Example 2: To verify the effectiveness of the proposed controller in the practical system, the network-based one-link manipulator obtained from [47] is considered as follows:

$$J\ddot{v} + F_v \dot{v} + G \sin(v) = \tau_v \quad (75)$$

where $\dot{v}$ and v are the velocity and position of the rigid link, respectively, $F_v = 1 \text{ N}\cdot\text{s}/\text{rad}$ denotes the overall damping

Fig. 4 Trajectories of x_2 and $\hat{x}_2$ in Example 1. Fig. 8 Trajectory of $\|\theta_2\|$ in Example 1. Fig. 5 Trajectories of χ_1 under different methods. Fig. 6 Trajectory of controller u in Example 1. Fig. 7 Trajectory of $\|\theta_1\|$ in Example 1.

coefficient, G denotes the gravity, $J = 1 \text{ kg} \cdot \text{m}^2$ denotes the rotational inertia of motor.

Define $u = \tau_v$, $x_1 = v$, and $x_2 = \dot{v}$, from manipulator system (75), one has

$$\begin{cases} \dot{x}_1 = x_2 + h_1(X) \\ \dot{x}_2 = u + h_2(X) \end{cases} \quad (76)$$

Table 1 Performance comparisons of different methods

Method	ITAE	IAE	Triggering numbers
Proposed method	1.08	1.29	227
Fixed threshold with $\rho_{fix} = 0.2$	1.18	1.39	354
Fixed threshold with $\rho_{fix} = 4.2$	1.46	1.43	232
Fixed threshold with $\rho_{fix} = 8$	1.56	1.31	235
Relative threshold	1.79	1.43	236

where $h_1(X) = 0.2 \sin(x_1) \cos(x_2)$ and $h_2(X) = -x_2 - 10 \sin(x_1)$. In (76), we intentionally introduce disturbed term $h_1(X)$. The desired reference signal is $y_d = 0.3 \sin(t)$.

In the simulation, choose the design parameters as $l_1 = 20$, $l_2 = 200$, $c_1 = 0.1$, $c_2 = 5$, $\bar{\rho} = 9$, $\bar{\omega} = 15$, $\omega_1 = 0.01$, $\iota_1 = \iota_2 = 0.1$, $t_r = 2$, $\mu_{tr} = 0.02$, $\mu_0 = 2.4$, $T^\dagger = 1$, $\rho_{ax} = 8$, $\rho_{in} = 0.2$, $\pi_1 = 0.01$, $\pi_2 = 0.02$, $\sigma_1 = \sigma_2 = 1$, $a_{11} = a_{12} = 0.025$, $a_{13} = 0.1$, $a_{23} = 0.9$, $a_{22} = 0.1$. $\theta_1^T \phi_1(\hat{X})$ and $\theta_2^T \phi_2(\hat{X})$ contain 20 nodes and 30 nodes respectively. For each of two neural networks, centers are spaced evenly in $[-2.5, 0.5] \times [-1, 7]$ and widths are equal to 8.8. The initial values are set as $x_1(0) = -2$, $x_2(0) = 0$, $\hat{x}_1(0) = -1.5$, $\hat{x}_2(0) = 1$, $\xi_k(0) = 0$ ($k = 1, 2$), $\theta_1(0) = 0_{20 \times 1}$ and $\theta_2(0) = 0_{30 \times 1}$.

The simulation results are given in Figs. 9–15, where the tracking performance and tracking error are shown in Fig. 9 and Fig. 12. The system state and estimation of them are shown in Fig. 10 and Fig. 11. Fig. 13 describes the control signal. Fig. 14 and Fig. 15 show that the trajectories of the norm of the adaptive parameters $\|\theta_1\|$ and $\|\theta_2\|$ remain bounded.

Furthermore, we select different design parameters t_r and μ_{tr} to demonstrate that these factors can affect the tracking performance via the proposed controller. The comparative results are given in Fig. 12, which is explained as follows.

1) For the design parameter $\mu_{tr} = 0.1$, a faster error convergence rate can be achieved by selecting the smaller t_r , and for $t_r = 2$, we can also obtain a faster transient process by choosing the smaller μ_{tr} , which verifies the conclusion in Remark 11.

2) Decreased the value of μ_{tr} will result in the better steady-state performance when $t_r = 2$.

Fig. 9 Trajectories of y_d and x_1 in Example 2.

Fig. 10 Trajectories of x_1 and $\hat{x}_1$ in Example 2.

Fig. 11 Trajectories of x_2 and $\hat{x}_2$ in Example 2.

Fig. 12 Trajectories of χ_1 under different cases.

5 Conclusion

This article has developed an event-triggered adaptive output-feedback controller for nonstrict-feedback nonlinear systems with given performance specifications, where a novel event-triggered mechanism with two thresholds and an improved speed transformation function have been designed. Neural state observer and neural networks have been adopted to ap-

Fig. 13 Trajectory of controller u in Example 2.

Fig. 14 Trajectory of $\|\theta_1\|$ in Example 2.

Fig. 15 Trajectory of $\|\theta_2\|$ in Example 2.

proximate unmeasured states and estimate uncertain functions, respectively. The structural property of RBF has been employed to deal with the algebraic loop problem caused by the nonstrict-feedback structure. Via flexibly incorporating command filtered technology, error compensation system with backstepping recursive method, a novel control strategy has been developed. All closed-loop signals are guaranteed to be bounded according to Lyapunov theory, and there is no Zeno-behavior. The developed control strategy can not only reduce the communication resources between the controller and actuator but also ensure that the output tracking error converges to a prescribed small region within preset time at predesigned converging rate. Finally, two simulation examples demonstrate the effectiveness and superiority of the developed control strategy. Further, we will extend the control strategy of this article to nonstrict-feedback switched nonlinear systems and nonstrict-feedback stochastic nonlinear systems.

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Conflict of interest The authors declare that they have no conflict of interest.

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