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. The salient features of the presented controller are fourfold: (1) The tracking error can converge to a preassigned small region at predesigned converging mode within prescribed time, and the prescribed time is independent of initial conditions of system. (2) The strict constraint on the initial value of tracking error is relaxed largely via an improved speed function. (3) The complexity of our control algorithm can be reduced since there is no control signal in the trigger condition. (4) 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 behavior 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 [1–9]). For stochastic strict-feedback systems, neural network controllers based on backstepping design procedure were developed in [6,7] by using neural observer and by utilizing event-triggered mechanism, respectively, where the barrier Lyapunov functions were employed to deal with state constraints. For fractional-order strict-feedback systems, two adaptive fault compensation controllers were developed in [8] by using static and dynamic event-triggering rules, whereas many practi-
finite-time method in [26–28], which has many merits. The tracking error converge within a finite time, the error is realized in a finite time. In order to make it cannot guarantee that the convergence of tracking consensus controller was proposed in [29] for nonlinearity. Based on state observer, a finite-time bipartite accuracy and faster convergence, attempts to give a new idea. Based on state observer, a finite-time bipartite consensus controller was proposed in [29] for nonlinear nonstrict-feedback multi-agent systems. Based on improved command-filtered backstepping technique, a finite-time controller was proposed in [30] for nonlinear systems with saturation constraint. By combining command-filtered backstepping method with a novel switching mechanism, a finite-time adaptive control strategy was designed in [31] for nonlinear systems with quantized input, where the switching mechanism was utilized to guarantee finite-time stability of error compensation system. Further, via incorporating command filter and prescribed performance control into backstepping design, a finite-time output-feedback control scheme was presented in [32] for nonstrict-feedback systems. It should be noted that the convergence time of tracking error, depending on the initial conditions of system, cannot be given arbitrarily in these works [26–32]. Fortunately, the work [33] 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 to design prescribed performance controller for MIMO strict-feedback systems in [34], where the tracking error can converge to a preassigned compact set in a pregiven time. It should be mentioned that \( \beta (0) = 1 \) in [34], where \( \beta (t) \) is a speed function, and if the speed function is directly utilized to constrain tracking error \( \chi (t) \), \( |\chi (0)| < 1 \) should be guaranteed, which is somewhat conservative in engineering applications. 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 [35–37] and for nonlinear nonstrict-feedback systems in [38], respectively. However, the results presented in [33–38] 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. In comparison with time-triggered strategy, event-triggered strategy can control data transmission on the basis of actual demands and system dynamics. Thus, some significant results about event-triggered control scheme can be found in [39–44]. Among them, the authors in [40] 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 [40] does not change during the control process. For further decreasing data transmission and increasing the effi-
ciency in resource utilization, an event-triggered adaptive controller was designed in [41] for strict-feedback systems with actuator failures by utilizing the neural state observer, where a varying threshold method was proposed to update the control signal. Via incorporating fuzzy wavelet neural network into state observer, an event-triggered control strategy with appointed-time tracking performance was proposed in [42] for strict-feedback systems, where the relative threshold mechanism was employed to save communication resources. Based on the linear state observer, an event-triggered adaptive neural network controller was proposed in [44] 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 with the observer-based finite-time adaptive tracking control in [4,22], observer-based prescribed performance tracking control in [45], the proposed output-feedback control scheme can ensure that not only the tracking error enters into the preassigned bounded set within a prescribed time, but also decay rate during the prescribed time interval is predesigned and controllable explicitly. Further, the prescribed time is independent of the initial condition of system states.
2. In comparison with the speed transformation function-based tracking control strategies with given performance specifications in [33,34], finite-time tracking control strategy with prescribed performance in [37] 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 [40] 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 command filtering technology is employed to deal with the “explosion of complexity” and “filtering error compensation” problems by utilizing filtering error compensating signal.

Notations: The $n$-dimensional Euclidean space is denoted as $\mathbb{R}^n$. The Euclidean norm for a vector or a matrix is represented as $\|\cdot\|$. $\text{sign}(\cdot)$ denotes the sign function. $\mathbb{Z}^+$ denotes positive integers. A function with $i$ continuous derivatives is defined as a $C^i$ function. $\mu^{(i)}(t)$ denotes the $i$-th derivatives of $\mu(t)$. $\lambda_{\min}(\cdot)$ and $\lambda_{\max}(\cdot)$ denote minimum eigenvalue and maximum eigenvalue, respectively.

2 Problem formulation

2.1 System description

Consider the following uncertain nonstrict-feedback system:
A novel event-triggered mechanism is designed to
\begin{align*}
\hat{x}_k &= x_{k+1} + h_k (X), \quad k = 1, 2, \ldots, n - 1 \\
\hat{x}_n &= u + h_n (X) \\
y &= x_1
\end{align*}
where \( X = [x_1, \ldots, x_n]^T \in \mathbb{R}^n \) and \( u \in \mathbb{R} \) represent plant state vector and control input, respectively. \( y \in \mathbb{R} \) is the output of plant. \( h_k (X), \quad k = 1, 2, \ldots, n, \) represents 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 \( X = [x_1, \ldots, x_n]^T \), the plant (1) is a nonstrict-feedback system. It is worth noting that the control methods developed in [5, 37] are effective for strict-feedback systems with full-state information. If the backstepping technology in [5, 37] 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 preassigned compact set at predesigned decay rate within a prescribed time.
3. A novel event-triggered mechanism is designed to effectively reduce data transmission between the controller and actuator and the Zeno behavior 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** [46] For hyperbolic tangent \( \tanh (\cdot) \), the following property holds

\[
0 \leq -\h \tanh \left( \frac{\h}{\sigma} \right) + |\h| \leq 0.2785 \sigma
\]

where \( \sigma > 0 \), \( \h \in \mathbb{R} \), \( -\h \tanh (\h/\sigma) \leq 0 \).

**Lemma 2** [47] Consider a continuous nonlinear function \( h (X) \) defined on a compact set \( \Omega \). Then, for \( \forall \varepsilon > 0 \), there exists a RBF neural network satisfying

\[
\sup_{x \in \Omega} |\h (X) - \theta^T \phi (X)| \leq \varepsilon
\]

where \( \theta = [\theta_1, \ldots, \theta_M]^T \) represents the ideal weight vector, \( \phi (X) = [p_1 (X), \ldots, p_M (X)]^T \) denotes the basis function vector, \( M > 1 \) is node number of neural network, and \( p_k (X) \) is constructed as \( p_k (X) = \exp \left\{ -(X - v_k)^T (X - v_k) / \gamma_k^2 \right\}, \quad k = 1, 2, \ldots, M \), \( v_k = [v_{k1}, \ldots, v_{kn}]^T \) is the center vector and \( \gamma_k \) 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 [33, 34], an improved speed function is introduced as follows:

\[
\mu (t) = \begin{cases} \frac{t_i^2}{(1 - \mu_0)(t_i - t)^3 \mu_0 + \mu_0 \mu_{ir} t_i^2}, & t \in [0, t_r] \\ \frac{\mu_0}{\mu_{ir}}, & t \in [t_r, +\infty) \end{cases}
\]

where \( \mu_0 \) and \( \mu_{ir} \leq 1 \) are positive parameters, \( t_r > 0 \) and \( \mu_0 \mu_{ir} \) denote settling time and ultimate bound of tracking error, respectively.

**Lemma 3** [34] 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 \( \mu \in [1/\mu_0, 1/\mu_0 \mu_{ir}] \) for \( t \in [0, +\infty) \).
2. At \( t = t_r \), \( \mu (t) \) reaches its maximum value \( 1/\mu_0 \mu_{ir} \) and remains to be \( 1/\mu_0 \mu_{ir} \) for \( t \in [t_r, +\infty) \).
3. For \( t \in [0, +\infty) \), \( \mu^{(i)} (t) \) \((i = 0, 1, 2)\) are \( C^2 \) and bounded, and \( \mu^{-1} (t) \dot{\mu} (t) \) is bounded.
Remark 4 Although some prescribed performance controllers, using exponential performance function \( \rho (t) = (\rho_0 - \rho_{\infty}) e^{-\tau t} + \rho_{\infty} \) (see [23–25]), 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.

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

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

From the definition of (5), we have

\[
\chi_1 = \frac{2}{\pi \mu} \arctan s_1 \tag{6}
\]

and

\[
\dot{\chi}_1 = -\frac{2\mu}{\pi \mu^2} \arctan s_1 + \frac{2}{\pi \mu} \frac{s_1}{1 + s_1^2} \tag{7}
\]

which yields

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

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

Remark 5 In contrast with the speed function in [33, 34], a new parameter \( \mu_0 \) 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 [14,48], a distinguishing feature, via using (5), is to ensure that the value of function \( \Xi \) 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 \( \chi_1 \) 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 \( \chi_1 \) can be realized indirectly.

2.3 Event-triggered mechanism

Inspired by [40], a novel event-triggered mechanism with two thresholds is designed as follows.

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

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

(9)

(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 \( \rho_{ax} > \rho_{in}, T_r > T^\dagger, t_q, q \in Z^+ \), 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 [40], the relative threshold method [44] 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, thereby contributing to a neural state observer. Before constructing the neural state observer, the nonstrict-feedback system (1) can be rewritten as

\[
\begin{align*}
\dot{X} & = AX + Ly + \sum_{k=1}^{n} B_k h_k (X) + Bu \\
y & = CX 
\end{align*}
\]

where

\[
A = \begin{bmatrix} -l_1 & & \\ & \ddots & \\ & & -l_n \end{bmatrix},
\]

\[
B_k = [0, 0, \ldots, 0, 1, 0, \ldots, 0]^T,
\]

\[
B = [0, \ldots, 0, 1]^T, 
\]

L = \begin{bmatrix} B_1 & \cdots & B_n \end{bmatrix}, 

C = [1, 0, \ldots, 0].

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

\[
A^T P + PA = -2Q. 
\]

Construct a neural observer as follows:

\[
\dot{\hat{X}} = A\hat{X} + Ly + \sum_{k=1}^{n} B_k \hat{h}_k \left( \hat{X} | \theta_k \right) + Bu 
\]

where \( \hat{X} = [\hat{x}_1, \ldots, \hat{x}_n]^T \) are defined to estimate \( X = [x_1, \ldots, x_n]^T \), 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 \( \hat{h}_k \left( \hat{X} | \theta \right) = \theta_k^T \phi_k \left( \hat{X} \right) \).

Similar to [6,49–51], the minimum approximation error \( \varepsilon_k \) and approximation error \( \delta_k \) are defined as

\[
\begin{align*}
\varepsilon_k & = h_k (X) - \hat{h}_k \left( \hat{X} | \theta_k^* \right) \\
\delta_k & = h_k (X) - \hat{h}_k \left( \hat{X} | \theta_k \right) 
\end{align*}
\]

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

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

\[
\dot{\tilde{X}} = A \tilde{X} + \sum_{k=1}^{n} B_k \left( h_k (X) - \hat{h}_k \left( \hat{X} | \theta_k \right) \right) 
\]

\[
= A \tilde{X} + \delta 
\]

where \( \delta = [\delta_1, \ldots, \delta_n]^T \).

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 [12,53], 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 track errors and command filtered system are defined:

\[
z_1 = s_1 \\
z_k = \dot{\hat{x}}_k - \lambda_k, \quad k = 2, \ldots, n
\]

where \( \lambda_k \) denotes the output of the following command filter with virtual controller \( \alpha_{k-1} \)

\[
\omega_{k-1} \dot{\lambda}_k + \lambda_k = \alpha_{k-1} 
\]

\[
\lambda_k (0) = \alpha_{k-1} (0), \quad k = 2, \ldots, n
\]

where \( \omega_{k-1} \) is a positive design parameter.

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

\[
\alpha_1 = -c_1 z_1 - 5a_1 \eta_1 \varphi - \theta_1^T \phi_1 (\tilde{x}_1) - \frac{2\mu}{\pi \mu^2} \arctan s_1 + \tilde{y}_d
\]

\[
\alpha_2 = -c_2 z_2 - 2a_2 \eta_2 - \theta_2^T \phi_2 (\tilde{x}_2) - l_2 \tilde{x}_1 + \tilde{\lambda}_2 - \varphi_1 z_1
\]

\[
\alpha_k = -c_k z_k - 2a_k \eta_k - \theta_k^T \phi_k (\tilde{x}_k) - l_k \tilde{x}_1 + \tilde{\lambda}_k - \varphi_{k-1} z_{k-1}, \quad k = 3, \ldots, n - 1
\]

\[
\alpha_n = -c_n z_n - a_n \eta_n - \theta_n^T \phi_n (\tilde{x}_n) - l_n \tilde{x}_1 + \tilde{\lambda}_n - \varphi_{n-1} z_{n-1}
\]

\[
\tau (t) = \alpha_n - \tilde{\rho} \tanh \left( \frac{\eta_n \tilde{\rho}}{\sigma} \right)
\]

\[
u (t) = \tau (t_q)
\]
Fig. 2 Block diagram of event-triggered control scheme with given performance specifications

where $\tilde{\rho} > \rho_{ax} > \rho_{in}, \sigma > 0, c_k > 0$ and $a_k > 0$ are design parameters for $k = 1, \ldots, n$. $\eta_k$ denotes the compensated tracking error given as

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

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

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

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

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

$$\dot{\xi}_1 = -c_1 \xi_1 + \Xi (\xi_2 + \lambda_1) - \Xi \tau_1 \text{sign} (\xi_1)$$
$$\dot{\xi}_2 = -c_2 \xi_2 - \Xi (\xi_1 + \lambda_2 - \xi_2 - \tau_2 \text{sign} (\xi_2))$$
$$\dot{\xi}_k = -c_k \xi_k - \xi_{k-1} + \lambda_{k+1} - \alpha_k + \xi_{k+1} - \tau_k \text{sign} (\xi_k)$$
$$\quad (k = 3, \ldots, n - 1)$$
$$\dot{\xi}_n = -c_n \xi_n - \xi_n - \tau_n \text{sign} (\xi_n)$$

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

According to the above design, the block diagram shown in Fig. 2 illustrates the signal flow of the presented control method.

Remark 9 Although the dynamic surface technique was employed in [22] 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 $\eta_1$ is given as

$$\dot{\eta}_1 = \dot{\xi}_1 - \dot{\hat{\xi}}_1$$
$$= \Xi \dot{\hat{x}}_2 + \Xi (z_2 + \lambda_2) + \Xi \left( \theta_1^T \phi_1 \left( \hat{X} \right) + \varepsilon_1 \right)$$
$$- \dot{\hat{y}}_d - \left( \frac{2 \hat{u}}{\pi \mu^2 \arctan s_1} \right) - \dot{\hat{\xi}}_1$$
$$= \Xi \dot{\hat{x}}_2 + \Xi (z_2 + \lambda_2) + \Xi \varepsilon_1 - \dot{\hat{\xi}}_1$$

$$\Xi$$ Springer
where $\tilde{\theta}_1 = \theta_1^* - \theta_1$. Constructing the Lyapunov function
\begin{equation}
V_1 = V_{\tilde{x}} + \frac{1}{2} \eta_1^2 + \frac{1}{2\pi_1} \tilde{\theta}_1^2
\end{equation}
where $V_{\tilde{x}} = \tilde{X}^T P \tilde{X}/2$. Its time derivative is obtained as
\begin{equation}
\dot{V}_1 = V_{\tilde{x}} + \eta_1 \dot{\eta}_1 - \frac{1}{\pi_1} \dot{\theta}_1^T \dot{\theta}_1
= -\tilde{X}^T Q \tilde{X} + \tilde{X}^T P \delta + \eta_1 (\mathcal{E} \tilde{x}_2 + \mathcal{E} \eta_2 + \mathcal{E} \alpha_1
+ \mathcal{E} (\theta_1^T \phi_1 (\tilde{x_1}))
+ \mathcal{E} \tilde{\theta}_1^T \phi_1 (\tilde{x_1}) + \mathcal{E} \tilde{\theta}_1^T \phi_1 (\tilde{x_1}) + \mathcal{E} \epsilon_1
+ \mathcal{E} \left( \frac{2\tilde{\mu}}{\pi_1 \mu^2} \arctan s_1 - \hat{y}_d \right)
+ c_1 \xi_1 + \mathcal{E} \xi_1 \text{sign} (\xi) \right) - \frac{1}{\pi_1} \dot{\theta}_1^T \dot{\theta}_1
\end{equation}

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
\begin{equation}
\eta_1 \mathcal{E} \theta_1^T \phi_1 (\tilde{x}) = \theta_1^T \phi_1 (\tilde{x}) \leq a_1 \eta_1^2 \mathcal{E}^2 + \| \theta_1 \|_2^2 M_1
\end{equation}
\begin{equation}
\eta_1 \mathcal{E} \epsilon_1 + \eta_1 \mathcal{E} \xi_1 \text{sign} (\xi)
\leq a_1 \eta_1^2 \mathcal{E}^2 + \frac{\hat{y}_d^2}{2a_1} + \frac{l_2^2}{2a_1}
\end{equation}

\begin{equation}
\eta_1 \mathcal{E} \tilde{x}_2 \leq \frac{a_1}{2} \eta_1^2 \mathcal{E}^2 + \frac{\| \tilde{X} \|_2^2}{2a_1}
\end{equation}
\begin{equation}
\tilde{X}^T P \delta \leq \frac{1}{2} \| P \delta \|_2^2 + \frac{\| \tilde{X} \|_2^2}{2}.
\end{equation}

Substituting (25)–(28) into (24) yields
\begin{equation}
\dot{V}_1 \leq -\tilde{X}^T \left( \lambda_{\text{min}} (Q) - \frac{1}{2a_1} - \frac{1}{2} \right) \tilde{X} + \mathcal{E} \eta_1 \eta_2
+ \mathcal{E} \eta_1 \bar{\theta}_1^T \phi_1 (\tilde{x}_1) - \frac{1}{\pi_1} \dot{\theta}_1^T \dot{\theta}_1 + \eta_1 \mathcal{E} \left( a_1
+ \frac{5a_1}{2} \eta_1 \mathcal{E} + \theta_1^T \phi_1 (\tilde{x}_1)
+ \frac{2\tilde{\mu}}{\pi_1 \mu^2} \arctan s_1 - \hat{y}_d + \frac{c_1 \xi_1}{\mathcal{E}} \right) + \| P \delta \|_2^2/2
+ \frac{\| \theta_1 \|_2^2 M_1}{a_1} + \frac{\hat{y}_d^2}{2a_1} + \frac{l_2^2}{2a_1}.
\end{equation}

Then, substituting $\alpha_1$ and $\dot{\theta}_1$ into (29), one has
\begin{equation}
\dot{V}_1 \leq -\mu_1 \tilde{X}^T \tilde{X} - c_1 (\cdot)_1^2 + \mathcal{E} \eta_1 \eta_2 + \frac{\alpha_1}{\pi_1} \dot{\theta}_1^T \dot{\theta}_1 + \Lambda (30)
\end{equation}

where $\Lambda_1 = \| P \delta \|_2^2/2 + \| \theta_1^* \|_2^2 M_1/a_1 + \hat{y}_d^2/2 (2a_1) + c_1 \xi_1/a_1$ and $\mu_1 = \lambda_{\text{min}} (Q) - 1/(2a_1) - 1/2 > 0$

Step 2: The derivative of $\eta_2$ is
\begin{equation}
\dot{\eta}_2 = z_2 - \xi_2
= \dot{\tilde{x}}_3 + \bar{h}_2 (\tilde{X} \| \theta_2 \| + l_2 \tilde{x}_1 - \lambda_2 - \xi_2
= z_3 + \lambda_3 + \theta_2^T \phi_2 (\tilde{X}) - \tilde{\theta}_2^T \phi_2 (\tilde{X}) + l_2 \tilde{x}_1 - \lambda_2
- \xi_2 - \theta_2^T \phi_2 (\tilde{X}_2) + \theta_2^T \phi_2 (\tilde{X}_2) + \tilde{\theta}_2^T \phi_2 (\tilde{X}_2)
\end{equation}

where $\tilde{\theta}_2 = \theta_2^* - \theta_2$. The Lyapunov function is constructed as
\begin{equation}
V_2 = V_1 + \frac{1}{2} \eta_2^2 + \frac{1}{2\pi_2} \tilde{\theta}_2^2.
\end{equation}

Then, we have
\begin{equation}
\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( \dot{\theta}_2^T \phi_2 (\tilde{X}) - \theta_2^T \phi_2 (\tilde{X}) \right)
\end{equation}

\begin{equation}
+ \tilde{\theta}_2^T \phi_2 (\tilde{X}_2) + l_2 \tilde{x}_1 - \lambda_2 + c_2 \xi_2 + \mathcal{E} \xi_1
+ c_2 \xi_2 \text{sign} (\xi_2)\right).
\end{equation}

Similar to step 1, we can obtain
\begin{equation}
\eta_2 \left( \theta_2^T \phi_2 (\tilde{X}) - \theta_2^T \phi_2 (\tilde{X}_2) \right) \leq a_2 \eta_2^2 + \frac{\| \theta_2 \|_2^2 M_2}{a_2}
\end{equation}
\begin{equation}
\eta_2 \text{sign} (\xi_2) \leq \frac{a_2}{2} \eta_2^2 + \frac{l_2^2}{2a_2}
\end{equation}
\begin{equation}
\eta_2 \text{sign} (\xi_2) \leq \frac{a_2}{2} \eta_2^2 + \frac{\tilde{\theta}_2^T \dot{\theta}_2 M_2}{2a_2}.
\end{equation}

Substituting (34)–(36) into (33) yields
\begin{equation}
\dot{V}_2 \leq -\mu_2 \tilde{X}^T \tilde{X} - c_1 \eta_2^2 + \frac{\alpha_1}{\pi_1} \dot{\theta}_1^T \dot{\theta}_1 + \Lambda_2 + \eta_2 \left( \alpha_2 + 2a_2 \eta_2 + \theta_2^T \phi_2 (\tilde{X}_2) + l_2 \tilde{x}_1 - \lambda_2
+ c_2 \xi_2 + \mathcal{E} \xi_1 \right)
\end{equation}

\begin{equation}
+ \xi_2 - \tilde{\theta}_2^T \phi_2 (\tilde{X}_2) - \tilde{\theta}_2^T \phi_2 (\tilde{X}_2)
+ \tilde{\theta}_2^T \phi_2 (\tilde{X}_2) + \tilde{\theta}_2^T \phi_2 (\tilde{X}_2)
\end{equation}

\begin{equation}
+ \frac{\tilde{\theta}_2^T \dot{\theta}_2 M_2}{2a_2} + \frac{\| \theta_2 \|_2^2 M_2}{a_2} + \frac{l_2^2}{2a_2}.
\end{equation}
Then, substituting $\alpha_2$ and $\theta_2$ into (37), one has
\[
V_2 \leq -\mu_1 \dot{X}^T \dot{X} - c_1 \eta_1^2 - c_2 \eta_2^2 + \eta_2 \eta_3^3
+ \frac{\sigma_1}{\pi_1} \dot{\theta}_1^T \theta_1 + \frac{\sigma_2}{\pi_2} \dot{\theta}_2^T \theta_2 + \frac{\dot{\theta}_2^T \theta_2 M_2}{2a_2} + \Lambda_2
\] (38)
where $\Lambda_2 = A_1 + \|\theta_2\|^2 M_2 / a_2 + \dot{\zeta}_k^2 / (2a_2)$.

Step $k$ ($k = 3, \ldots, n - 1$): The derivative of $\eta_k$ is
\[
\dot{\eta}_k = \ddot{\eta}_k + \dot{h}_k (\dot{X} | \theta_k) + l_k \dot{x}_1 - \dot{\lambda}_k - \dot{\xi}_k
\]
\[
= z_{k+1} + \dot{\lambda}_k + \dot{\xi}_k + \dot{\theta}_k^T \phi_k (\dot{X}) - \dot{\theta}_k^T \phi_k (\dot{X})
\]
(39)
\[
+ l_k \dot{x}_1 - \dot{\lambda}_k - \dot{\xi}_k - \dot{\theta}_k^T \phi_k (\dot{X})
\]
\[
+ \dot{\theta}_k^T \phi_k (\dot{X}_k) + \dot{\theta}_k^T \phi_k (\dot{X}_k)
\]
where $\dot{\theta}_k = \dot{\theta} - \theta$. The Lyapunov function is constructed as
\[
V_k = V_{k-1} + \frac{1}{2} \eta_k^2 + \frac{1}{2\pi_k} \theta_k^2
\]
(40)
Then, we have
\[
\dot{V}_k = \dot{V}_{k-1} + \eta_k \dot{\eta}_k - \frac{1}{\pi_k} \dot{\theta}_k^T \dot{\theta}_k
\]
\[
= \dot{V}_{k-1} - \frac{1}{\pi_k} \dot{\theta}_k^T \dot{\theta}_k
\]
\[
+ \eta_k (\dot{h}_k (\dot{X} | \theta_k) + l_k \dot{x}_1 - \dot{\lambda}_k - \dot{\xi}_k)
\]
\[
- \dot{\theta}_k^T \phi_k (\dot{X}_k) + \dot{\theta}_k^T \phi_k (\dot{X}_k)
\]
(41)
Similar to step 2, we can obtain
\[
\eta_k \left( \theta_k^T \phi_k (\dot{X}) - \theta_k^T \phi_k (\dot{X}_k) \right) \leq \alpha_k \eta_k^2 + \frac{\| \theta_n^2 \|^2 M_k}{\alpha_k}
\]
(42)
\[
\eta_k \text{ sign } (\xi_k) \leq \frac{\alpha_k}{2} \eta_k^2 + \frac{\dot{\eta}_k^2}{2a_k}
\]
(43)
\[
\eta_k \dot{\theta}_k \text{ sign } (\xi_k) \leq \frac{\alpha_k}{2} \eta_k^2 + \frac{\dot{\theta}_k^2 \theta_k M_k}{2a_k}
\]
(44)
Substituting (42)–(44) into (41) yields
\[
\dot{V}_k \leq \dot{V}_{k-1} + \eta_k \eta_{k+1} + \eta_k (\alpha_k + 2a_2 \eta_k)
\]
\[
+ \dot{\theta}_k \phi_k (\dot{X}_k) + l_k \dot{x}_1 - \dot{\lambda}_k + c_k \dot{\xi}_k + \dot{\xi}_k - \dot{\theta}_k \phi_k (\dot{X}_k)
\]
(45)
\[
+ \eta_k \dot{\theta}_k \phi_k (\dot{X}_k) - \frac{1}{\pi_k} \frac{\dot{\theta}_k \theta_k M_k}{2a_k}
\]
\[
+ \frac{\| \theta_n^2 \|^2 M_k}{\alpha_k} + \frac{\dot{\eta}_k^2}{2a_k}
\]
Then, substituting $\alpha_k$ and $\theta_2$ into (45), one has
\[
\dot{V}_k \leq -\mu_1 \dot{X}^T \dot{X} - \sum_{i=1}^{k} c_i \eta_i^2 + \eta_k \eta_{k+1}
\]
(46)
\[
+ \sum_{i=1}^{k} \frac{\sigma_i}{\pi_i} \dot{\theta}_i \theta_i + \sum_{i=2}^{k} \frac{\dot{\theta}_i \theta_i M_i}{2a_i} + \Lambda_k
\]
where $\Lambda_k = \Lambda_{k-1} + \| \theta_n^2 \|^2 M_k / a_k + \dot{\zeta}_k^2 / (2a_k)$.

Remark 10: It can be noticed that the function $\dot{h}_k (\dot{X} | \theta_k)$ in the neural observer (13) contains the whole state estimate $\dot{X} = [\dot{x}_1, \ldots, \dot{x}_n]^T$. To ensure that only partial state estimate $\dot{X}_k = [\dot{x}_1, \ldots, \dot{x}_k]^T$ is included in the virtual controller $\alpha_k$, we employ Young’s inequality and the structural property of RBF to deal with the whole variable $\dot{X}$, which solves the problem of algebraic loop. Compared with [14, 17, 18], 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 $\eta_n$ is
\[
\dot{\eta}_n = \dot{x}_n = \dot{\xi}_n
\]
(47)
\[
= u + \dot{h}_n (\dot{X} | \theta_n) + l_n \dot{x}_1 - \dot{\lambda}_n - \dot{\xi}_n
\]
\[
= u + \dot{h}_n (\dot{X} | \theta_n) + \dot{\theta}_n^T \phi_n (\dot{X}) + \dot{\theta}_n \phi_n (\dot{X})
\]
(47)
\[
+ l_n \dot{x}_1 - \dot{\lambda}_n - \dot{\xi}_n.
\]
Choose the Lyapunov function
\[
V_n = V_{n-1} + \frac{1}{2} \eta_n^2 + \frac{1}{2\pi_n} \dot{\theta}_n^2.
\]
(48)
Then, we have
\[
\dot{V}_n = \dot{V}_{n-1} + \eta_n \dot{\eta}_n - \frac{1}{\pi_n} \dot{\theta}_n \theta_n
\]
(49)
\[
= \dot{V}_{n-1} - \frac{1}{\pi_n} \dot{\theta}_n^T \theta_n + \eta_n (u + \dot{h}_n (\dot{X} | \theta_n) + \dot{\theta}_n^T \phi_n (\dot{X}) + \dot{\theta}_n \phi_n (\dot{X})
\]
\[
+ l_n \dot{x}_1 - \dot{\lambda}_n + c_k \dot{\xi}_k + \dot{\xi}_k - l_n \dot{x}_1
\]
(47)
\[
\text{sign } (\xi_n) .
\]
Applying Young’s inequality yields
\[
\eta_n \text{ sign } (\xi_n) \leq \frac{\alpha_k}{2} \eta_n^2 + \frac{\dot{\eta}_n^2}{2a_n}
\]
(50)
\[-\eta_n \hat{\theta}_n^T \phi_n (\hat{X}) \leq \frac{a_n}{2} \eta_n^2 + \frac{\hat{\theta}_n^T \hat{\theta}_n M_n}{2a_n}. \]  

(51)

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

\[
\dot{V}_n \leq \dot{V}_{n-1} + \eta_n \left( u + a_n \eta_n + \hat{\theta}_n^T \phi_n (\hat{X}) + l_n \bar{x}_1 - \bar{\lambda}_n + c_n \bar{\xi}_n + \bar{\xi}_{n-1} \right) + \eta_n \hat{\theta}_n^T \phi_n (\hat{X})
\]

\[-\frac{1}{\pi_n^2} \dot{\theta}_n^T \hat{\theta}_n + \frac{\hat{\theta}_n^T \hat{\theta}_n M_n}{2a_n} + \frac{\bar{\eta}_n^2}{2a_n}. \]  

(52)

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

\[ |\tau (t) - u (t)| < \rho_{a\kappa}. \]  

(53)

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

\[ u (t) = \tau (t) - \kappa (t) \rho_{a\kappa}. \]  

(54)

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

\[
\dot{V}_n \leq \dot{V}_{n-1} + \eta_n \left( \alpha_n - \tilde{\rho} \tanh \left( \frac{\eta_n \tilde{\rho}}{\sigma} \right) \right) - \kappa (t) \rho_{a\kappa}
\]

\[ + a_n \eta_n + \hat{\theta}_n^T \phi_n (\hat{X}) + l_n \bar{x}_1
\]

\[-\bar{\lambda}_n + c_n \bar{\xi}_n + \bar{\xi}_{n-1} \right) + \eta_n \hat{\theta}_n^T \phi_n (\hat{X})
\]

\[-\frac{1}{\pi_n^2} \dot{\theta}_n^T \hat{\theta}_n + \frac{\hat{\theta}_n^T \hat{\theta}_n M_n}{2a_n} + \frac{\bar{\eta}_n^2}{2a_n}. \]  

(55)

Substituting \( \alpha_n \) and \( \hat{\theta}_n \) into (55) yields

\[
\dot{V}_n \leq -\mu_1 \bar{X}^T \bar{X} - \sum_{k=1}^{n} c_k \eta_n^2 + \sum_{k=1}^{n} \frac{\sigma_k}{\pi_k} \hat{\theta}_n^T \theta_k
\]

\[ + \sum_{k=2}^{n} \frac{\hat{\theta}_n^T \theta_k M_k}{2a_k} + \Lambda_n + \eta_n \left( -\tilde{\rho} \tanh \left( \frac{\eta_n \tilde{\rho}}{\sigma} \right) \right)
\]

\[-\kappa (t) \rho_{a\kappa}. \]  

(56)

where \( \Lambda_n = \Lambda_{n-1} + \bar{\eta}_n^2/(2a_n) \). From \( \hat{\theta}_n = \theta_n^* - \theta_k \), one has

\[
\hat{\theta}_n^T \theta_k \leq \frac{1}{2} \theta_n^T \theta_k - \frac{1}{2} \hat{\theta}_n^T \hat{\theta}_k \]  

(57)

and then

\[
\sum_{k=1}^{n} \frac{\sigma_k}{\pi_k} \hat{\theta}_n^T \theta_k \leq \sum_{k=1}^{n} \frac{\sigma_k}{2\pi_k} \hat{\theta}_n^T \hat{\theta}_k + \sum_{k=1}^{n} \frac{\sigma_k}{2\pi_k} \theta_n^* \theta_k
\]

(58)

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

\[
\dot{V}_n \leq -\mu_1 \bar{X}^T \bar{X} - \sum_{k=1}^{n} c_k \eta_n^2 + \sum_{k=1}^{n} \frac{\sigma_k}{\pi_k} \hat{\theta}_n^T \theta_k
\]

\[ + \sum_{k=2}^{n} \frac{\hat{\theta}_n^T \theta_k M_k}{2a_k} + \Lambda_n - \eta_n \tilde{\rho} \tanh \left( \frac{\eta_n \tilde{\rho}}{\sigma} \right)
\]

\[ + |\eta_n \tilde{\rho}| \leq -\mu_1 \bar{X}^T \bar{X} - \sum_{k=1}^{n} c_k \eta_n^2 - \left( \frac{\sigma_1}{2\pi_1} \hat{\theta}_n^T \hat{\theta}_1 \right)
\]

\[ + \sum_{k=2}^{n} \left( \frac{\sigma_k}{2\pi_k} - \frac{M_k}{2a_k} \right) \hat{\theta}_n^T \theta_k + \Lambda'_n \]  

(59)

where \( \Lambda'_n = \Lambda_n + \sum_{k=1}^{n} \sigma_k \theta_n^* \theta_k^s / 2\pi_k + 0.2785 \sigma \).

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 preassigned small region near zero within prescribed time \( t_r \) at predesigned converging mode during the period \( t \in [0, t_r] \) and all the signals \( x_k, \bar{x}_k, z_k, \eta_k, \bar{\xi}_k, \bar{\xi}_{k-1}, k = 1, \ldots, n, \tau (t) \) and \( u (t) \) are bounded. In addition, \( \forall q \in Z^+ \), there is a positive instant \( t_N > 0 \) satisfying \( \{t_{q+1} - t_q \} \geq t_N \).

**Proof** The analysis process is divided into the following steps.

(1) The boundedness of filtering errors \( \lambda_k \) for \( k = 2, \ldots, n \) is proved for \( k = 2, \ldots, n \). From (17), we have

\[ \lambda_k (t) = \lambda_k (0) e^{-\omega_{k-1}} + \int_0^t \frac{1}{\omega_{k-1}} e^{-\frac{\tau - \tilde{\tau}}{\omega_{k-1}}} \alpha_{k-1} (\tilde{\tau}) \, d \tilde{\tau} \]  

(60)

where \( k = 2, \ldots, n \). According to [52], \( e^{-\frac{t - \tilde{t}}{\omega_{k-1}}} / \omega_{k-1} \) is a delta function located at \( t \) when \( \omega_{k-1} \to 0 \). Furthermore, we have

\[ \lambda_k (t) \to \lambda_k (0) e^{-\frac{t}{\omega_{k-1}}} + \alpha_{k-1} (t) a \omega_{k-1} \to 0. \]  

(61)

For \( \lambda_{k-1} > 0 \) and \( \forall t \geq 0 \), there exists \( \lambda_{\delta k} > 0 \) such that

\[ |\lambda_k (t) - \alpha_{k-1} (t)| \leq \lambda_k (0) e^{-\frac{t}{\omega_{k-1}}} + \lambda_{\delta k} \]  

(62)
where \( \omega_{k-1} \in [0, \lambda \delta_k] \). Therefore, if \( \omega_{k-1} \) is set to be small enough, \( |\lambda_k(t) - \alpha_{k-1}(t)| \) is bounded, which means that \( |\lambda_k(t) - \alpha_{k-1}(t)| < \varepsilon_{\lambda,k} \) with \( \varepsilon_{\lambda,k} > 0 \).

(2) By means of bounded filtering errors, the stability of error compensation system (21) is guaranteed. We choose the Lyapunov function as 

\[
V = \sum_{k=1}^{n} \frac{\xi_k^2}{2}.
\]

Then, the derivative of \( V \) is obtained as

\[
\dot{V} = -c_1\xi_1^2 + \sum_{i=1}^{n} \xi_i \xi_i^2 + \sum_{i=1}^{n} \left( \lambda_i - \alpha_i \right) \xi_i - \Xi \| \xi \|.
\]

Furthermore, the design parameters should be selected so that

\[
\ anonym[46x698] = -\ \Theta V + \Lambda_n' \]

where \( \Theta = \min \{ 2\mu_1/\lambda_{\max} (P), 2c_k, \sigma_k, \sigma_k - 2\pi_kM_k/(2a_k) \} \).

Consequently, from (66), we have

\[
V (t) \leq V (0) e^{-\Theta t} + \frac{\Lambda_n'}{\Theta}.
\]

Then, it can be obtained that \( \eta_k, \hat{\theta}_k, \xi_k \) and \( \tilde{\theta}_k \) are bounded for \( k = 1, \ldots, n \). From \( z_k = \eta_k + \xi_k, \tilde{z}_k \) is bounded. Next, \( x_1 \) and \( \lambda_1 \) are bounded as \( y_i \) is bounded, which implies that \( \alpha_1 \) and \( \lambda_2 \) are bounded. Similarly, we can prove \( x_k, \tilde{x}_k, \alpha_k, \tau (t) \) 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

\[
|\chi| < \frac{1}{\mu} \left\{ \frac{(1-\mu_{\eta})(\tau-t)^{3} \mu_{\eta} + \mu_{\mu_{\mu_{\mu}}}}{t_{\sigma}} \right\}, t \in [0, t_{r}), \mu_{\mu_{\mu_{\mu}}}, t \in (t_{r}, +\infty)
\]

which implies that the error \( |\chi| \) reduces to \( \mu_0 \mu_{\mu_{\mu}} \) within prescribed time \( t_{r} \) at predefined converging mode governed by \( (1 - \mu_{\eta})(t_{r} - t)^{3} \mu_{\eta} / t_{\sigma}^2 \).

(3) The boundedness of all signals is demonstrated via the whole Lyapunov function, which ensures the prescribed performance for tracking error. We construct the whole Lyapunov function as

\[
V = V_n + V_\xi.
\]

The derivative of \( V \) is obtained as

\[
\dot{V} \leq -\frac{2\mu_1}{\lambda_{\max} (P)} \dot{X}^T P \dot{X} + \sum_{k=1}^{n} \frac{c_k \eta_k^2}{2} \left( \sigma_1 + \sum_{k=2}^{n} \left( \sigma_k - \frac{2\pi_k M_k}{2a_k} \right) \right) \left( \dot{\theta}_k \right) \left( \dot{\theta}_k \right) \leq -\Theta V + \Lambda_n'
\]

\[
\ anonym[46x698] = \min \{ 2\mu_1/\lambda_{\max} (P), 2c_k, \sigma_1, \sigma_k, 2\pi_k M_k/(2a_k) \}.
\]

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, \( \gamma (t_q) = 0 \) and \( \lim_{t \rightarrow q+1} \gamma (t) \geq \rho_0 \), so the lower bound of event-triggered time intervals \( t_{\kappa} \) must satisfy \( t_{\kappa} \geq 2 \rho_0 / \gamma > 0 \). Therefore, the Zeno behavior is ruled out.

Remark 11 Compared with the existing works, we further emphasize the merits of our results.
To obtain faster tracking process, we can appropriately increase $c_k$ and $\sigma_k$ for $k = 1, 2, \ldots, n$ and decrease $\pi_k$ and $\omega_{j-1}$ for $j = 2, 3, \ldots, n$. However, from the definitions of $\Theta$ and $\Lambda''$, larger $\sigma_k$ or smaller $\pi_k$ may affect tracking accuracy. In addition, the error compensation system can asymptotically converge to zero by introducing $l_k$.

Observer parameters $l_k$ ($k = 1, 2, \ldots, n$) need to be selected appropriately, such that a Hurwitz matrix $A$ can be obtained. Then, there exist a positive definite matrix $P^T = P$ and a given matrix $Q^T = Q > 0$ so that $A^T P + PA = -2Q$. In addition, the state estimation accuracy can be improved remarkably by increasing $l_k$. Nevertheless, if $l_k$ is excessively big, the magnitude of control signal may be too large.

It can be demonstrated from (69) that in the interval $t \in [t_q, t_{q+1})$, if the value of $\mu_0$ determined by the initial tracking error $\chi_1(0)$ does not change, then the converging rate of $|\chi_1|$ is affected not only by $\mu_t$, but also by $t_r$. A faster tracking process can be achieved by decreasing $\mu_t$, or shortening pre-scribed time $t_r$, which will be shown in the later simulation comparison experiment.

**Remark 13** 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
\[
\begin{align*}
\dot{x}_1 &= x_2 + h_1(X) \\
\dot{x}_2 &= u + h_2(X) \\
y &= x_1 
\end{align*}
\]

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 $x_1(0) = 1.5$, $x_2(0) = 1$, $\dot{x}_1(0) = 0$ and $\dot{x}_2(0) = 0$. The desired reference signal is $y_d = \sin(t)$.

Construct the following neural state observer
\[
\begin{align*}
\dot{\hat{x}}_1 &= \hat{x}_2 + l_1(y - \hat{x}_1) + \theta_1^T \phi_1(\hat{X}) \\
\dot{\hat{x}}_2 &= u + l_2(y - \hat{x}_1) + \theta_2^T \phi_2(\hat{X}) 
\end{align*}
\]

where the observer gain vector is designed as $L = [l_1, l_2] = [38, 60]$. $\theta_1^T \phi_1(\hat{X})$ 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
\[
\begin{align*}
\dot{\theta}_1 &= \pi_1 \eta_1 \phi_1(\hat{x}_1) - \sigma_1 \theta_1 \\
\dot{\theta}_2 &= \pi_2 \eta_2 \phi_2(\hat{X}) - \sigma_2 \theta_2
\end{align*}
\]
with $\theta_1 (0) = 0.125 \times 1$ and $\theta_2 (0) = 0.125 \times 1$.

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

$$
\alpha_1 = -\frac{c_1 z_1}{\Sigma} - \frac{5d_1}{2} \eta_1 \Sigma - \theta_1^T \phi_1 (\hat{x}_1)
- \frac{2\mu}{\pi \mu^2} \arctan s_1 + \hat{y}_d
$$

$$
\alpha_2 = -c_2 z_2 - a_2 \eta_2 - \theta_2^T \phi_2 (\hat{X})
- \bar{\tau}_1 + \hat{\lambda}_2 - \Sigma \xi_1
$$

(74)

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

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

where $\bar{\rho}$ is the command filter system given as

$$\omega_1 \hat{\xi}_2 + \lambda_2 = \alpha_1, \quad \lambda_2 (0) = \alpha_1 (0)
$$

(75)

and the error compensation mechanism is constructed as

$$\hat{\xi}_1 = -c_1 \xi_1 + \Sigma \xi_2 + \Sigma (\lambda_2 - \alpha_1) - \Sigma \xi_2 \tanh (\xi_1)
$$

$$\hat{\xi}_2 = -c_2 \xi_2 - \Sigma \xi_1 - \xi_2 \tanh (\xi_2)
$$

(76)

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

In the simulation, choosing the design parameters as $c_1 = 0.1, c_2 = 15, \bar{\rho} = 9, \sigma = 15, \omega_1 = 0.01,
\nu_1 = \nu_2 = 0.1, \tau_r = 5, \mu_r = 0.05, \mu_0 = 2.5, T^+ = 1,$
$\rho_{ax} = 8.9, \rho_{in} = 0.2, \pi_1 = \pi_2 = 0.01, \sigma_1 = \sigma_2 = 1,$
$\alpha_1 = 0.04, \alpha_2 = 1.$ The sampling period is 0.001 s.

To show the superiority of the event-triggered mechanism, simulation experiments by using time-triggered mechanism (TTM), fixed threshold mechanism (FTM) and relative threshold mechanism (RTM) are included for comparison. The FTM can be obtained from [56], and it is given as follows:

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

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

(77)

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

where $\bar{\rho} = 9$ and $\rho_{fix} = 0.2.$

The RTM from [41] is given as follows:

$$
\tau_{rel} (t) = -\left( 1 + \sigma_{rel} \right) \alpha_2 \tanh \left( \frac{\eta_2 \sigma_{rel}}{\sigma_{rel}} \right)
+ \bar{\rho}_{rel} \tanh \left( \frac{\eta_2 \bar{\rho}_{rel}}{\sigma_{rel}} \right)
$$

(78)

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

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

where $\bar{\rho}_{rel} = 0.2, \rho_{rel} = 0.6, \sigma_{rel} = 1.5$ and $\rho_{rel} = 0.05.$

The relevant design parameters of TTM, FTM and RTM are the same as the proposed method. Figures 3, 4, 5, 6, 7, 8 and 9 describe simulation results, where Fig. 3 shows that both the proposed method and TTM can realize trajectory tracking. Figure 6 shows that the tracking error $\chi_1$ converges to a small region around zero within a prescribed time $\tau_r$ at pre-designed decay rate. It also points out that compared with FTM and RTM, both the proposed method and TTM can obtain superior tracking performance according to faster response and smaller oscillation. Figures 4 and 5 show the designed neural observer can estimate the system states. Control signals of the proposed method and TTM are presented in Fig. 7, and it can be discovered that for the proposed method, the control signals sent to the actuator are piecewise constants, which can greatly reduce data sending and promote resource usage. Figures 8 and 9 show that the trajectories of the norm of adaptive parameters $|\theta_1| |\theta_2|$ are bounded.

Furthermore, performance comparisons of the presented method, TTM, FTM and RTM are summarized in Table 1. The integrated time absolute and integrated absolute error in [57], labeled as ITAE and IAE, is employed to evaluate dynamic performance and stable precision of tracking controllers, respectively, where

$$
\text{ITAE} = \int_0^{20} \nu |\chi_1 (\nu)| d \nu \quad \text{and} \quad \text{IAE} = \int_0^{20} |\chi_1 (\nu)| d \nu.
$$

From Table 1, we can see that the proposed method and TTM achieve almost the same dynamic performance and stable precision, whereas the proposed method requires less triggering numbers. In addition, Table 1 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 [56] is considered as follows:

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

(79)

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 coefficient, $G$ denotes the gravity, $J = 1 \text{kg} \cdot \text{m}^2$ denotes the rotational inertia of motor.
Define $u = \tau v, x_1 = v, \text{ and } x_2 = \dot{v}$, from manipulator system (79), one has

$$\begin{align*}
\dot{x}_1 &= x_2 + h_1(X) \\
\dot{x}_2 &= u + h_2(X)
\end{align*}$$

(80)

where $h_1(X) = 0.2 \sin(x_1) \cos(x_2)$ and $h_2(X) = -x_2 - 10 \sin(x_1)$. In (80), 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 $l_1 = 20, l_2 = 500, c_1 = 0.1, c_2 = 15, \rho = 9, \sigma = 15, \omega_1 = 0.01, \iota_1 = \iota_2 = 0.1, \iota_r = 2, \mu_r = 0.1, \mu_0 = 2.4, T^+ = 1, \rho_{ax} = 8, \rho_{an} = 0.2, \pi_1 = \pi_2 = 0.01, \sigma_1 = 10, \sigma_2 = 8, a_1 = 0.04, a_2 = 0.5, \theta_1^T \phi_1(\dot{X}) \text{ and } \theta_2^T \phi_2(\dot{X})$ contain 30 nodes and 60 nodes, respectively. For each of two neural networks, centers are spaced evenly in...
The trajectories of the norm of adaptive actuator are piecewise constants. Figures 15 and 14, and it demonstrates that the control signals sent to the proposed method and PPCEM are depicted in Fig. 13, 14, 15 and 16, where Fig. 10 shows that both the tracking performance according to smaller steady-state error and faster response. The system states and estimation of them are shown in Figs. 11 and 12. Control signals of the proposed method can realize superior tracking performance and state transformation are given as follows:

\[
\omega_p(t) = (\omega_p - \omega_\infty)e^{-\sigma_p t} + \omega_\infty
\]

\[
\beta_p(t) = \frac{1}{2} \ln \frac{\hat{\omega}_p + 1}{\hat{\omega}_p} \tag{81}
\]

where \(\omega_p = 2.4, \omega_\infty = 0.24\) and \(\sigma_p = 2.5\). The event-triggered mechanism in PPCEM is fixed threshold approach. The relevant design parameters of PPCEM are the same as the proposed method and are given as \(l_{P1} = 20, l_{P2} = 500, c_{P1} = 0.1, c_{P2} = 15, \hat{\rho}_p = 9, \omega_\rho = 15, \omega_p = 0.01, \iota_{P1} = \iota_{P2} = 0.1, \pi_{P1} = \pi_{P2} = 0.01, \sigma_{P1} = 10, \sigma_{P2} = 8, a_{P1} = 0.04, a_{P2} = 0.5, \rho_{P_t} = 0.2\).

The simulation results are given in Figs. 10, 11, 12, 13, 14, 15 and 16, where Fig. 10 shows that both the proposed method and PPCEM can achieve trajectory tracking. Figure 13 shows that compared with PPCEM, the proposed method can realize superior tracking performance according to smaller steady-state error and faster response. The system states and estimation of them are shown in Figs. 11 and 12. Control signals of the proposed method and PPCEM are depicted in Fig. 14, and it demonstrates that the control signals sent to the actuator are piecewise constants. Figures 15 and 16 show that the trajectories of the norm of adaptive parameters \(\|\theta_1\|\) and \(\|\theta_2\|\) remain bounded. In additional, Table 2 means that the proposed method is better than PPCEM since it has the lower ITAE and IAE while requiring less triggering numbers.

Table 1 Performance comparisons of different methods

| Method     | ITAE | IAE | Triggering numbers |
|------------|------|-----|--------------------|
| Proposed method | 0.721 | 0.739 | 276                |
| TTM        | 0.706 | 0.75 | 20,000             |
| FTM [56]   | 0.723 | 0.756| 390                |
| RTM [41]   | 0.753 | 0.76 | 328                |

The initial values are set as \(x_1(0) = -2, x_2(0) = -3, \hat{x}_1(0) = -1.5, \hat{x}_2(0) = 2, \xi_k(0) = 0(k = 1, 2), \theta_1(0) = 0_{30 \times 1} \text{ and } \theta_2(0) = 0_{60 \times 1}\).

To show the superiority of the proposed method, the prescribed performance controller with event-triggered mechanism (PPCEM) in [40] is employed to compare control performance, where the neural observer and variable separation method are also added for fair comparison. For PPCEM, the prescribed performance function and state transformation are given as follows:

\[
\omega_p(t) = (\omega_p - \omega_\infty)e^{-\sigma_p t} + \omega_\infty
\]

\[
\beta_p(t) = \frac{1}{2} \ln \frac{\hat{\omega}_p + 1}{\hat{\omega}_p} \tag{81}
\]

where \(\omega_p = 2.4, \omega_\infty = 0.24\) and \(\sigma_p = 2.5\). The event-triggered mechanism in PPCEM is fixed threshold approach. The relevant design parameters of PPCEM are the same as the proposed method and are given as \(l_{P1} = 20, l_{P2} = 500, c_{P1} = 0.1, c_{P2} = 15, \hat{\rho}_p = 9, \omega_\rho = 15, \omega_p = 0.01, \iota_{P1} = \iota_{P2} = 0.1, \pi_{P1} = \pi_{P2} = 0.01, \sigma_{P1} = 10, \sigma_{P2} = 8, a_{P1} = 0.04, a_{P2} = 0.5, \rho_{P_t} = 0.2\).
Furthermore, we select different design parameters $t_r$ and $\mu_{tr}$ to demonstrate that these factors can affect the tracking performance via the proposed controller. The comparative results are given in Fig. 17, 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 $\mu_{tr}$, which verifies the conclusion in Remark 12.

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

**Table 2** Performance comparisons of different methods

| Method          | ITAE | IAE | Triggering numbers |
|-----------------|------|-----|--------------------|
| Proposed method | 0.733| 0.791| 154                |
| PPCEM [40]      | 1.301| 0.926| 245                |

**Fig. 17** Trajectories of $\chi_1$ 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 approximate 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 preassigned small region within prescribed 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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Data availability The authors can confirm that all relevant data are included in the article.

Declarations

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

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