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Event-triggered finite-time command-filtered tracking control for nonlinear time-delay cyber physical systems against cyber attacks*

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Abstract: This article addresses the secure finite-time tracking problem via event-triggered command-filtered control for nonlinear time-delay cyber physical systems (CPSs) subject to cyber attacks. Under the attack circumstance, the output and state information of CPSs is unavailable for the feedback design, and the classical coordinate conversion of the iterative process is incompetent in relation to the tracking task. To solve this, a new coordinate conversion is proposed by considering the attack gains and the reference signal simultaneously. By employing the transformed variables, a modified fractional-order command-filtered signal is incorporated to overcome the complexity explosion issue, and the Nussbaum function is used to tackle the varying attack gains. By systematically constructing the Lyapunov–Krasovskii functional, an adaptive event-triggered mechanism is presented in detail, with which the communication resources are greatly saved, and the finite-time tracking of CPSs under cyber attacks is guaranteed. Finally, an example demonstrates the effectiveness.

Key words: Cyber physical systems; Finite-time tracking; Event-triggered; Command-filtered control; Attacks
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1 Introduction

In recent years, physical systems have been tightly integrated with cyber components via network communication channels. These systems are denominated as cyber physical systems (CPSs) (Wang YN et al., 2016; Ge XH et al., 2023a). While considering the fact that CPSs are vulnerable to cyber attacks, the security problem is recognized to be one of the main concerns (Ding et al., 2021; Wang R et al., 2021; Xie et al., 2023). Among the various attacks, deception attacks are characterized by the injection of false data into sensors or actuators to change the authenticity of transmitted signals and system data, which will seriously threaten the security of CPSs (Guan and Ge, 2018; Xiao et al., 2022). To deal with the deception attacks, a novel detection strategy was presented in Ge XH et al. (2019) for a discrete system subject to data deception attacks on sensor communication links and the system dynamics. In Chen WD et al. (2022), a coordinate conversion was proposed to achieve the tracking task of CPSs with deception attacks by considering the attack gain.

It is known that in the network environment, the continuous transmission of data results in the

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generation of a lot of redundant data, thereby causing the imposition of unnecessary load upon network communication (Samy et al., 2023; Yang SH et al., 2023; Zhang et al., 2023). Thus, the event-triggered mechanism has been established to reduce the communication rate, and many important results have been received (Ju et al., 2022; Liu et al., 2022; Yang D et al., 2022; Ge XH et al., 2023b; Hu et al., 2023). For example, Xu and Guo (2022) proposed an event-triggered scheme to handle the multiple network attacks and obtained the length rate and the upper bound of attack frequency. With the use of a sampled-data model, Zhang et al. (2020) introduced a logic processor to receive sampled data and designed resilient controllers for systems under denial-of-service attacks. Based on the dead zone operator, Wang YC et al. (2022) designed an event-triggered adaptive controller to ensure boundedness of the tracking error in the mean square in the sense of attacks. It needs to be noted that while, on one hand, the above mentioned results focus on the asymptotic performance corresponding to time approaching infinity, on the other hand, it is always a key objective in practice to reach the steady performance within a limited period of time under the given operating conditions (Wei et al., 2021; Chen WB et al., 2022; Ning et al., 2023). Through a command-filtered inversion technique, faster and more accurate control was obtained in Song et al. (2022b). In Kazemi et al. (2022), a finite-time state estimator was introduced for CPSs with unknown inputs and sensor attacks to estimate the state of the CPS in a predefined finite time. One approach for achieving finite-time performance that needs to be particularly emphasized is the deployment of the coordinate conversion technique, which was introduced in Kazemi et al. (2022) and Song et al. (2022b) for continuing the iterative control. However, since the system output and state data are corroded by attackers, and only the compromised data are available for feedback design, the classical coordinate conversion cannot be directly applied to the controlled systems. Ascertainment of the means to address the mismatching output signal is difficult when solving the finite-time tracking issue of CPSs under the attacks.

On the other hand, the foregoing important results involve repeated differentiation of virtual control, which results in a complexity explosion issue (Li ZJ and Zhao, 2021). The use of the dynamic surface method and command-filtered technology can help avoid this problem (Choi and Yoo, 2020). Considering the influences of time delays, Li M et al. (2022) used the Lyapunov–Krasovskii (LK) functional to incorporate time delays and designed an adaptive event-triggered controller based on a command filter. In Wang X et al. (2023), an event-based dynamic surface control method was adopted to deal with the influence of deception attacks and time delays. Compared with the common integer-order (IO) filter used in the abovementioned research, fractional-order (FO) control is characterized by the unique advantage of historical memory, and can thus provide another option for the improvement of the system performance. Song et al. (2022a) incorporated coordinate conversion and an improved fractional-order command filtering (FOCF) technique to deal with deception attacks, and overcame the computational complexity difficulty. It is stressed that although many FO design methods characterized by a combination of FO properties and IO techniques have been reported in the literature, to our knowledge, studies reporting results pertaining to the finite-time command-filtered tracking issue for nonlinear time-delay CPSs via event-triggered mechanism with cyber attacks are rare.

With the above mentioned rationale serving as a motivation, the present research aims to solve the event-triggered finite-time tracking problem for the nonlinear time-delay CPSs against unknown cyber attacks. By proposing a new coordinate conversion technique, and combining fractional calculus with the command-filtered methods, all signals of the closed-loop system are bounded and the output of CPSs tracks the desired reference signal in a finite time.

1. The systematical design procedure, encompassing the introduction of the FO command filter, the construction of the LK functional, the utilization of the Nussbaum function, and the design of the adaptive event-triggered mechanism, is presented in detail. Based on the above mentioned strategies, the finite-time tracking of CPSs under cyber attacks is guaranteed with limited network communication resources.

2. A new coordinate conversion is proposed to cope with the coupling effects between the reference signal and the cyber attacks. By embodying the reference signal and the compromised variables

simultaneously, the transformed state is used as the available data for the tracking design. Compared with the approaches adopted in Chen WD et al. (2022) and Song et al. (2022b), the new coordinate transformation method is suitable for more general time-delay CPSs with non-strict feedback structures.

3. An improved FO command filter is proposed using FO calculus. It realizes the finite-time tracking of time-delay CPSs, overcomes the complexity explosion problem, and improves the filtering performance.

2 Problem description and preliminaries

2.1 Problem description

Consider a nonlinear time-delay CPS given by

$$\begin{cases} \dot{x}_i(t) = x_{i+1}(t) + f_i(X(t)) + g_i(\bar{x}_{i,\tau(t)}(t)) + d_i(t), \\ \dot{x}_n(t) = u(t) + f_n(X(t)) + g_n(\bar{x}_{n,\tau(t)}(t)) + d_n(t), \end{cases} \tag{1}$$

where $i = 1, 2, ..., n-1$, $u(t) \in \mathbb{R}$ is the control input, and $X(t) = (x_1(t), x_2(t), \ldots, x_n(t))^{\mathrm{T}} \in \mathbb{R}^n$ and $\bar{x}_{i,\tau(t)}(t) = (x_1(t-\tau_1(t)), x_2(t-\tau_2(t)) \ldots, x_i(t-\tau_i(t)))^{\mathrm{T}}$ with $i = 1, 2, \ldots, n$ are the unavailable state variables and delayed state variables, respectively. The delays are bounded, satisfying $0 < \tau_i \leq \bar{\tau}_i < \infty$, $\dot{\tau}_i \leq \bar{\tau}_{\mathrm{id}} < 1$, with $\bar{\tau}_i > 0$ and $\bar{\tau}_{\mathrm{id}} > 0$ being unknown constants. In addition, the nonlinear functions $g_i\big(\bar{x}_{i,\tau(t)}(t)\big)$ and $f_i\big(X(t)\big)$ are smooth but unknown. $d_i(t)$ is the unknown disturbance, and $|d_i(t)| \leq \bar{d}_i$ with $\bar{d}_i$ being a positive constant. For system (1), we consider the deception attack cases, which are modeled by

$$\begin{cases} \breve{x}_1(t) = x_1(t) + \lambda_1(t), \\ \breve{x}_i(t) = x_i(t) + \lambda_i(t), \end{cases} \tag{2}$$

where $i = 2, 3, ..., n$, $\lambda_1(t)$ is the first attack of x_1, $\lambda_i(t)$ is the attack of x_i, and $\breve{x}_i$ is the available system state after attack.

Assumption 1 The deception attacks are expressed as $\lambda_1(t) = \varpi_1(t)x_1(t)$, $\lambda_i(t) = \varpi(t)x_i(t)$, where the weight $\varpi_1(t)$ is known, $\varpi(t)$ is unknown, and $1 + \varpi_1(t) \neq 0$, $1 + \varpi(t) \neq 0$. We suppose that the unknown positive constants $\bar{\varpi}$ and $\bar{\varpi}_M$ are the upper bounds of $|\varpi(t)|$ and $|\dot{\varpi}(t)|$, respectively.

Remark 1 Assumption 1 is a standard and common requirement used in the existing results; see, for example, Kazemi et al. (2022) and Song et al. (2022b). According to (2), we can obtain $\breve{x}_1 = (1+\varpi_1)x_1$ and $\breve{x}_i = (1+\varpi)x_i$. If $1 + \varpi_1 = 0$ and $1 + \varpi = 0$, the available compromised states will vanish. In this particular case, there are no available signals that can be used for the control design to guarantee the security of CPSs. Furthermore, to ensure the tracking task against the attacked output, it is necessary to suppose that the attack weight of the first step differs from that in other steps.

The objective of the research is to ensure event-triggered finite-time tracking control of system (1) under attacks (2).

2.2 Preliminaries

The function $F_i(\Delta_i)$ is a continuous one within a compact set Ω_Δ. Then, it can be approximated by neural networks (NNs) satisfying

$$F_i(\Delta_i) = \Xi_i^{\mathrm{T}} \Pi_i(\Delta_i) + o_i, \tag{3}$$

where o_i is an approximation error and Δ_i expresses the input vector of NNs, $\Xi_i = (\Xi_{i1}, \Xi_{i2}, \ldots, \Xi_{il})^{\mathrm{T}} \in \mathbb{R}^l$ and $\Pi_i(\Delta_i) = \big(\Pi_{i1}(\Delta_i), \Pi_{i2}(\Delta_i), \ldots, \Pi_{il}(\Delta_i)\big)^{\mathrm{T}} \in \mathbb{R}^l$ denote the basis function and the weight vector respectively, and

$$\Pi_{il}(\Delta_i) = \exp\Big(-\frac{(\Delta_i - \sigma_{il})^{\mathrm{T}}(\Delta_i - \sigma_{il})}{b_{il}^2}\Big), \tag{4}$$

with l being the neuron number, and b_{il} and σ_{il} the corresponding width and center respectively.

Assumption 2 Ξ_i and o_i satisfy the relationship $\|\Xi_i\| \leq \bar{\Xi}_i$ and $|o_i| \leq \bar{o}_i$ with $\bar{\Xi}_i$ and $\bar{o}_i$ being the unknown constants.

Lemma 1 (Li ZJ and Zhao, 2021) For an NN with $\Delta = (x_1, x_2, \ldots, x_n)^{\mathrm{T}}$ and $\Pi(\Delta) = \big(\Pi_1(\Delta), \Pi_2(\Delta), \ldots, \Pi_l(\Delta)\big)^{\mathrm{T}}$ being its input vector and basis function vector respectively, the following inequality holds:

$$\|\Pi(\Delta)\| \leq \|\Pi(\Delta_p)\|, \tag{5}$$

where $\Delta_p = (x_1, x_2, \ldots, x_p)$ with $1 \leq p \leq n$.

Definition 1 (Song et al., 2022a) Let us define a function $\Gamma(1-\alpha) = \int_0^{+\infty} s^{-\alpha}\mathrm{e}^{-s}\mathrm{d}s$, $0 < \alpha < 1$. For a function $f(t)$, the fractional derivative of order α with Caputo's definition is given by

$$D^\alpha f(t) = \int_{t_0}^{t} \frac{f'(\tau)}{\Gamma(1-\alpha)(t-\tau)}\mathrm{d}\tau. \tag{6}$$

Definition 2 (Kazemi et al., 2022) A continuous even function is called a Nussbaum-type function if

$$\lim_{s\to\infty}\sup\frac{1}{s}\int_0^s N(t)\mathrm{d}t=+\infty, \tag{7}$$

$$\lim_{s\to\infty}\inf\frac{1}{s}\int_0^s N(t)\mathrm{d}t=-\infty. \tag{8}$$

Lemma 2 (Chen WD et al., 2022) We consider a smooth Nussbaum-type function $N(\xi)$, and the smooth functions $V(t)$ and $\xi(\cdot)$ defined on $[0,t_\mathrm{s})$ and $V(t)\geq 0, \forall t\in[0,t_\mathrm{s})$. If

$$V(t)\leq m_1+\mathrm{e}^{-m_2 t}\int_0^t\left(\bar{n}(\varsigma)N(\xi)+1\right)\dot{\xi}\mathrm{e}^{m_2\varsigma}\mathrm{d}\varsigma \tag{9}$$

holds $\forall t\in[0,t_\mathrm{s})$, with two constants $m_1>0$, $m_2>0$, and $\bar{n}(\cdot)$ being a time-varying parameter taking values in a non-trivial closed interval $I=[l^-,l^+]$, then $\xi(t)$, $V(t)$, and $\int_0^t\bar{n}(\varsigma)N(\xi)\dot{\xi}\mathrm{d}\varsigma$, $t\in[0,t_\mathrm{s})$ are bounded.

Lemma 3 (Ge SS and Tee, 2007) For any real numbers $\mu_1,\mu_2>0$, $0<q<1$, a finite-time Lyapunov stability condition is given by $\dot{V}(t)+\mu_1 V(x)+\mu_2 V^q(x)\leq 0$, where the finite-time $T_s\leq T_0+\left(1/(\mu_1(1-q))\right)\ln\left(\left(\mu_1 V^{1-q}(T_0)+\mu_2\right)/\mu_2\right)$.

Lemma 4 (Li M et al., 2022) Let $\pi_1\in\mathbb{R}^n$, $\pi_2\in\mathbb{R}^m$, and $g:\mathbb{R}^n\times\mathbb{R}^m\mapsto\mathbb{R}$ be a continuous function. There are smooth scalar functions $C(\pi_1)\geq 0$ and $D(\pi_2)\geq 0$ such that

$$|g(\pi_1,\pi_2)|\leq C(\pi_1)+D(\pi_2). \tag{10}$$

By using Lemma 4, for the terms $g_j(\bar{x}_{j,\tau(t)})$, one can deduce

$$|g_j(\bar{x}_{j,\tau(t)})|\leq\sum_{s=1}^{j}\varTheta_{j,s}\left(x_{s,\tau_s(t)}\right), \tag{11}$$

where $x_{s,\tau_s(t)}=x_s(t-\tau_s(t))$ and $\varTheta_{j,s}(\cdot)$ are continuous functions.

Lemma 5 (Song et al., 2022b) For $z\in\mathbb{R}$ and a positive constant ϖ, it holds that

$$0\leq|z|-\frac{z^2}{\sqrt{z^2+\varpi^2}}<\varpi. \tag{12}$$

Lemma 6 (Song et al., 2022a) For any real variables s_1 and s_2 and any positive numbers ς_1,ς_2, and ϱ, it holds that

$$|s_1|^{\varsigma_1}|s_2|^{\varsigma_2}\leq\frac{\varsigma_1}{\varsigma_1+\varsigma_2}\varrho|s_1|^{\varsigma_1+\varsigma_2}+\frac{\varsigma_1}{\varsigma_1+\varsigma_2}\varrho^{\frac{-\varsigma_1}{\varsigma_2}}|s_2|^{\varsigma_1+\varsigma_2}. \tag{13}$$

3 Main results

From the attacks (2), one has

$$\begin{cases} x_1(t)=\gamma_1\check{x}_1(t),\\ x_i(t)=\gamma\check{x}_i(t), \end{cases} \tag{14}$$

where $\gamma_1=(1+\varpi_1)^{-1}$, $\gamma=(1+\varpi)^{-1}$. From Assumption 1, one obtains that γ is bounded by $\gamma_\mathrm{m}\leq|\gamma|\leq\gamma_\mathrm{M}$, where γ_m and γ_M are some positive constants. We propose the following new coordinate conversion to construct a controller under deception attacks:

$$\begin{cases} z_1=x_1-y_\mathrm{d},\\ z_i=x_i-\gamma\theta_{i-1}, \end{cases} \tag{15}$$

where y_d is the reference signal, θ_{i-1} $(i=2,3,\ldots,n)$ are filtered signals of the virtual control law $\hbar_{i-1}$ $(i=2,3,\ldots,n)$, and $\hbar_{i-1}$ will be designed below.

Remark 2 In traditional tracking control, the output signal is not attacked, and thus the output signal and the tracking signal are matched. In CPSs under deception attacks, the matched condition is no longer available for the attacked output signal. To realize the tracking control for the attacked system, it is assumed that, unlike the case with other steps, the attack signal for the first step is known. We propose a new coordinate conversion, including the reference signal and the attack signal simultaneously, to ensure the tracking task for the CPSs under attacks.

From (15), one can deduce

$$\begin{cases} \check{z}_1=\check{x}_1-\frac{1}{\gamma_1}y_\mathrm{d},\\ \check{z}_i=\check{x}_i-\theta_{i-1}, \end{cases} \tag{16}$$

where the filtered signal θ_{i-1} is calculated with the FO filter:

$$\begin{cases} D^\alpha\lambda_{1,i-1}=\varGamma_{1,i-1},\\ \quad\varGamma_{1,i-1}=-\alpha_{1,i-1}(\lambda_{1,i-1}-\hbar_{i-1})^{\beta_1}\\ \qquad\qquad-\alpha_{2,i-1}(\lambda_{1,i-1}-\hbar_{i-1})^{\beta_2}+\lambda_{2,i-1},\\ D^\alpha\lambda_{2,i-1}=-\alpha_{3,i-1}(\lambda_{1,i-1}-\hbar_{i-1})^{\beta_3}, \end{cases} \tag{17}$$

where $0<\beta_1<1$, $\beta_2>1$, $0<\beta_3<1$, $\alpha_{1,i-1}>0$, $\alpha_{2,i-1}>0$, $\alpha_{3,i-1}>0$ are some constants, and D^α defined in (6) is the fractional operator. The order α takes its value in $(0,1)$. The input of the filter is virtual control law $\hbar_{i-1}$, and the outputs are $\theta_{i-1}=\lambda_{1,i-1}$ and $D^\alpha\theta_{i-1}=\varGamma_{1,i-1}$.

Remark 3 Compared with IO control, the unique aspect of FO control is its historical memory behavior, which enables the system to obtain better precision and a greater degree of design freedom. FOCF is used to obtain the filtered signal of the virtual control law. This method can improve the filtering performance by reducing the filtering error, and also can overcome the computational pressure brought by the traditional iterative method.

We define the filter error $\epsilon_i = \theta_i - \hbar_i$. Then, the signals that compensate for the filtering errors would be as follows:

$$\begin{cases} \dot{\psi}_i = -a_{1,i}\psi_i - a_{2,i}\psi_i^{2q-1} - H\psi_i + \epsilon_i, \\ \dot{\psi}_n = -a_{1,n}\psi_n - a_{2,n}\psi_n^{2q-1}, \end{cases} \tag{18}$$

where $H = (|\check{z}_i\epsilon_i| + a_{3,i}\epsilon_i^2)/||\psi_i||^2$ and $a_{l,i}$ $(l = 1,2,3, i = 1,2,\ldots,n-1)$ are the design parameters.

Step 1: According to system (1), coordinate transformations (15), and the definition of the filter error $\epsilon_i = \theta_i - \hbar_i$, one can deduce the time derivative of z_1 as

$$\begin{aligned} \dot{z}_1 =& \dot{x}_1 - \dot{y}_\mathrm{d} \\ =& z_2 + \gamma\theta_1 + f_1(X) + g_1(\bar{x}_{1,\tau(t)}) + d_1 - \dot{y}_\mathrm{d} \\ =& z_2 + \gamma(\epsilon_1 + \hbar_1) + f_1(X) + g_1(\bar{x}_{1,\tau(t)}) + d_1 - \dot{y}_\mathrm{d}. \end{aligned} \tag{19}$$

The Lyapunov function is chosen as follows:

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2}\tilde{\eta}_1^2 + \frac{1}{2}\psi_1^2 + \frac{1}{2}\tilde{\varLambda}_1^2 + W_1, \tag{20}$$

with $W_1 = \frac{\mathrm{e}^{b_{11}\overline{\tau}_1}}{1-\overline{\tau}_{1d}}\mathrm{e}^{-b_{11}t}\int_{t-\tau_1(t)}^{t}\mathrm{e}^{b_{11}s}\varTheta_{1.1}^2(x_1(s))\mathrm{d}s$, b_{11} being a positive constant, and $\tilde{\eta}_1 = \eta_1 - \hat{\eta}_1$, $\tilde{\varLambda}_1 = \varLambda_1 - \hat{\varLambda}_1$ with η_1, $\varLambda_1$ to be defined and $\hat{\eta}_1$, $\hat{\varLambda}_1$ being their estimates.

Let us denote for simplicity $\phi_1 = (\mathrm{e}^{b_{11}\overline{\tau}_1}/(1-\overline{\tau}_{1d}))\varTheta_{1.1}^2(x_1(t))$. Following the definition of W_1 provided above, one can obtain the derivative of W_1 as

$$\dot{W}_1 \le -b_{11}W_1 + \phi_1 - \varTheta_{1.1}^2(x_{1,\tau(t)}). \tag{21}$$

By adding and subtracting the two terms $\tanh^2(z_1/l_1)\phi_1/z_1$ and z_1^{2q}, it follows from Lemma 6 and (19) that

$$\begin{aligned} \dot{V}_1 =& -z_1\Big(z_2 + \gamma(\epsilon_1 + \hbar_1) + f_1(X) + g_1(\bar{x}_{1,\tau(t)}) \\ &+ d_1 - \dot{y}_\mathrm{d}\Big) - \tilde{\eta}_1\dot{\hat{\eta}}_1 + \psi_1\dot{\psi}_1 - \tilde{\varLambda}_1\dot{\hat{\varLambda}}_1 + \dot{W}_1 \\ \le& -z_1^{2q} + \frac{1}{2}z_1^2 + \frac{1}{2}z_2^2 + z_1\gamma\epsilon_1 + z_1\gamma\hbar_1 - z_1\dot{y}_\mathrm{d} \\ &+ \check{z}_1\Big(F_1(X, y_\mathrm{d}) + D_1\Big) + z_1 g_1(\bar{x}_{1,\tau(t)}) - \tilde{\eta}_1\dot{\hat{\eta}}_1 \\ &+ \psi_1\dot{\psi}_1 - \tilde{\varLambda}_1\dot{\hat{\varLambda}}_1 + \dot{W}_1 - 2\tanh^2\left(\frac{z_1}{l_1}\right)\phi_1, \end{aligned} \tag{22}$$

where $F_1(X,\gamma_1) = \gamma_1\big(f_1(X) + z_1^{2q-1}\big) + \big(2\gamma_1\tanh^2(\frac{z_1}{l_1})\phi_1\big)/z_1$, $D_1 = \gamma_1 d_1(t)$. From Assumption 1 and $|d_i(t)| \le \bar{d}_i$, one can obtain $|D_1| \le \varLambda_1$ with $\varLambda_1$ being an unknown constant.

Since the term $F_1(X,\gamma_1)$ is unknown, the NNs are used to approximate this uncertain term, and the following equality can be obtained:

$$F_1(\varDelta_1) = \varXi_1^\mathrm{T}\varPi_1(\varDelta_1) + o_1, \tag{23}$$

where $\varDelta_1 = (X,\gamma_1)$, and o_1 is the approximation error. It is noted that $\varDelta_1$ is the attacked state and cannot be used for the feedback design. To continue the design process, $\varDelta_1$ is replaced by the system state $\check{\varDelta}_1 = (\check{X},\gamma_1)$, and (23) is rewritten as

$$\begin{aligned} F_1(X,\theta_1,\gamma_1) =& \varXi_1^\mathrm{T}\varPi_1(\check{\varDelta}_1) + \varXi_1^\mathrm{T}\big(\varPi_1(\varDelta_1) \\ &- \varPi_1(\check{\varDelta}_1)\big) + o_1. \end{aligned} \tag{24}$$

Using (11), one can derive $z_1 g_1(\bar{x}_{1,\tau(t)}) \le \frac{1}{4}z_1^2 + \varTheta_{1.1}^2(x_{1,\tau(t)})$. Then, invoking (22)–(24) yields

$$\begin{aligned} \dot{V}_1 \le& -z_1^{2q} + \frac{3}{4}z_1^2 + \frac{1}{2}z_2^2 + z_1\gamma\epsilon_1 + z_1\gamma\hbar_1 \\ &+ \check{z}_1\Big(\varXi_1^\mathrm{T}\varPi_1(\check{\varDelta}_1) + D_1\Big) + \check{z}_1\varPsi_1 \\ &- b_{11}W_1 - \check{z}_1\gamma_1\dot{y}_\mathrm{d} - \tilde{\eta}_1\dot{\hat{\eta}}_1 + \psi_1\dot{\psi}_1 \\ &- \tilde{\varLambda}_1\dot{\hat{\varLambda}}_1 + \left(1 - 2\tanh^2\left(\frac{z_1}{l_1}\right)\right)\phi_1, \end{aligned} \tag{25}$$

where $\varPsi_1 = \varXi_1^\mathrm{T}\Big(\varPi_1(\varDelta_1) - \varPi_1(\check{\varDelta}_1)\Big) + o_1$.

Recalling Assumptions 1 and 2, one can infer that $|\varPsi_1| \le \bar{\varPsi}_1$ with $\bar{\varPsi}_1 > 0$ being a constant. Therefore, it holds that

$$\check{z}_1\varPsi_1 \le c_1\check{z}_1^2 + \frac{\bar{\varPsi}_1^2}{4c_1}, \tag{26}$$

where c_1 is a positive constant. Besides, it follows from Lemmas 1, 5, and 6 that

$$\begin{aligned} &\check{z}_1\Big(\varXi_1^\mathrm{T}\varPi_1(\check{\varDelta}_1) + D_1\Big) \\ \le& \frac{\check{z}_1^2\eta_1\varPi_1^\mathrm{T}(\check{\varDelta}_1)\varPi_1(\check{\varDelta}_1)}{2\delta_1^2} + \frac{\delta_1^2}{2} + \varpi_1\varLambda_1 + \frac{\varLambda_1\check{z}_1^2}{\sqrt{\check{z}_1^2 + \varpi_1^2}} \\ \le& \frac{\check{z}_1^2\eta_1\varPi_1^\mathrm{T}(\check{\varDelta}_1^*)\varPi_1(\check{\varDelta}_1^*)}{2\delta_1^2} + \frac{\delta_1^2}{2} + \varpi_1\varLambda_1 + \frac{\varLambda_1\check{z}_1^2}{\sqrt{\check{z}_1^2 + \varpi_1^2}}, \end{aligned} \tag{27}$$

where $\eta_1 = \|\varXi_1\|^2$ and $\check{\varDelta}_1^* = \check{x}_1$.

The adaptive laws and virtual controller are given by

$$\begin{cases} \hbar_1 = N(\xi_1)\bar{\hbar}_1 + \psi_1, \\ \bar{\hbar}_1 = k_1 \check{z}_1 \gamma_1^2 + \dfrac{\check{z}_1 \hat{\eta}_1 \Pi_1^{\mathrm{T}}(\check{\Delta}_1^*) \Pi_1(\check{\Delta}_1^*)}{2\delta_1^2} + 2c_1 \check{z}_1 \\ \quad + \dfrac{\hat{\Lambda}_1 \check{z}_1}{\sqrt{\check{z}_1^2 + \varpi_1^2}} - \gamma_1 \dot{y}_{\mathrm{d}}, \\ \dot{\hat{\eta}}_1 = \dfrac{\check{z}_1^2 \Pi_1^{\mathrm{T}}(\check{\Delta}_1^*) \Pi_1(\check{\Delta}_1^*)}{2\delta_1^2} - \rho_{11}\hat{\eta}_1, \\ \dot{\hat{\Lambda}}_1 = \dfrac{\check{z}_1^2}{\sqrt{\check{z}_1^2 + \varpi_1^2}} - \rho_{12}\hat{\Lambda}_1, \end{cases} \tag{28}$$

where $\dot{\xi}_1 = \check{z}_1 \bar{\hbar}_1$, and k_1, ρ_{11}, and ρ_{12} are some positive constants. Substituting (18) and (26)–(28) into (25) yields

$$\begin{aligned} \dot{V}_1 \leq & - z_1^{2q} - \bar{k}_1 z_1^2 - b_{11} W_1 + \frac{1}{2} z_2^2 \\ & + \Big(\bar{n}_1(t) N(\xi_1) + 1\Big)\dot{\xi}_1 + \rho_{11}\tilde{\eta}_1\hat{\eta}_1 + \rho_{12}\tilde{\Lambda}_1\hat{\Lambda}_1 \\ & - \bar{a}_{1,1}\psi_1^2 - a_{2,1}\psi_1^{2q} - \bar{a}_{3,1}\epsilon_1^2 \\ & + \Big(1 - 2\tanh^2\Big(\frac{z_1}{l_1}\Big)\Big)\phi_1 + \zeta_1, \end{aligned} \tag{29}$$

where $\bar{n}_1(t) = \gamma_1\gamma$, $\bar{k}_1 = k_1 - 1$, $\bar{a}_{1,1} = a_{1,1} - (\frac{1}{2} + 2\gamma_{\mathrm{M}}^2)$, $\bar{a}_{3,1} = a_{3,1} - (\frac{1}{2} + 2\gamma_{\mathrm{M}}^2) - \frac{1}{4c_1}$, $\zeta_1 = \frac{\bar{\Psi}_1^2}{4c_1} + \frac{\delta_1^2}{2} + \varpi_1\Lambda_1$.

For the terms $\rho_{11}\tilde{\eta}_1\hat{\eta}_1$ and $\rho_{12}\tilde{\Lambda}_1\hat{\Lambda}_1$ in (29), the following inequalities hold:

$$\begin{cases} \rho_{11}\tilde{\eta}_1\hat{\eta}_1 \leq -\bar{\rho}_{11}\tilde{\eta}_1^2 + \bar{\rho}_{11}\eta_1^2, \\ \rho_{12}\tilde{\Lambda}_1\hat{\Lambda}_1 \leq -\bar{\rho}_{12}\tilde{\Lambda}_1^2 + \bar{\rho}_{12}\Lambda_1^2, \end{cases} \tag{30}$$

where $\bar{\rho}_{1i} = \rho_{1i}/2$ $(i = 1, 2)$. Furthermore, by defining $s_1 = 1$, $s_2 = \tilde{\eta}_1^2/2$, $\varsigma_1 = 1 - q$, $\varsigma_2 = q$, $\varrho = q^{q/(1-q)}$, one can obtain from Lemma 6 that

$$\begin{cases} \Big(\dfrac{1}{2}\tilde{\eta}_1^2\Big)^q \leq (1-q)\varrho + \dfrac{1}{2}\tilde{\eta}_1^2, \\ \Big(\dfrac{1}{2}\tilde{\Lambda}_1^2\Big)^q \leq (1-q)\varrho + \dfrac{1}{2}\tilde{\Lambda}_1^2. \end{cases} \tag{31}$$

Similarly, one can obtain

$$W_1^q \leq (1-q)\varrho + W_1. \tag{32}$$

Substituting (30)–(32) into (29), one can deduce

$$\begin{aligned} \dot{V}_1 \leq & - \bar{k}_1 z_1^2 - z_1^{2q} + \frac{1}{2} z_2^2 + \Big(\bar{n}_1(t) N(\xi_1) + 1\Big)\dot{\xi}_1, \\ & - \bar{a}_{1,1}\gamma_1^2 - a_{2,1}\gamma_2^{2q} - \bar{a}_{3,1}\epsilon_1^2 + \bar{\zeta}_1 - \bar{b}_{11} W_1 \\ & - b_{12} W_1^q + \Big(1 - 2\tanh^2\Big(\frac{z_1}{l_1}\Big)\Big)\phi_1 - \frac{\bar{\rho}_{11}}{2}\tilde{\eta}_1^2 \\ & - \bar{\rho}_{11}\Big(\frac{1}{2}\tilde{\eta}_1^2\Big)^q - \frac{\bar{\rho}_{11}}{2}\tilde{\Lambda}_1^2 - \bar{\rho}_{11}\Big(\frac{1}{2}\tilde{\Lambda}_1^2\Big)^q, \end{aligned} \tag{33}$$

where b_{12} is a positive constant, $\bar{b}_{11} = b_{11} - b_{12} > 0$, and $\bar{\zeta}_1 = \zeta_1 + \bar{\rho}_{11}\eta_1^2 + \bar{\rho}_{12}\Lambda_1^2 + (\bar{\rho}_{11} + \bar{\rho}_{12} + b_{12})(1-q)\varrho$.

Step i $(i = 2, 3, \ldots, n-1)$: From (1) and (15), and the definition of the filter error $\epsilon_i = \theta_i - \hbar_i$, one calculates

$$\begin{aligned} \dot{z}_i = & z_{i+1} + \gamma(\epsilon_i + \hbar_i) + f_i(X) + g_i(\bar{x}_{i,\tau(t)}) + d_i \\ & - \dot{\gamma}\theta_{i-1} - \gamma\dot{\theta}_{i-1}. \end{aligned} \tag{34}$$

The Lyapunov function is chosen as follows:

$$V_i = V_{i-1} + \frac{1}{2}z_i^2 + \frac{1}{2}\tilde{\eta}_i^2 + \frac{1}{2}\psi_i^2 + \frac{1}{2}\tilde{\Lambda}_i^2 + W_i, \tag{35}$$

with $W_i = \sum_{j=1}^{i}\big(\mathrm{e}^{b_{i1}\overline{\tau}_j}/(1-\overline{\tau}_{j\mathrm{d}})\big)\mathrm{e}^{-b_{i1}t}\int_{t-\tau_j(t)}^{t}\mathrm{e}^{b_{i1}s} \cdot \Theta_{i.j}^2\big(x_j(s)\big)\mathrm{d}s$, b_{i1} a positive constant, $\tilde{\eta}_i = \eta_i - \hat{\eta}_i$, $\tilde{\Lambda}_i = \Lambda_i - \hat{\Lambda}_i$ with η_i, Λ_i to be defined and $\hat{\eta}_i$, $\hat{\Lambda}_i$ being their estimates.

Let us denote $\phi_i = \sum_{j=1}^{i}\frac{\mathrm{e}^{b_{i1}\overline{\tau}_j}}{1-\overline{\tau}_{j\mathrm{d}}}\Theta_{i.j}^2\big(x_j(t)\big)$. Then, one can obtain the derivative of W_i as

$$\dot{W}_i \leq -b_{i1}W_1 + \phi_i - \sum_{j=1}^{i}\Theta_{i.j}^2(x_{j,\tau(t)}). \tag{36}$$

Similar to (22), one deduces

$$\begin{aligned} \dot{V}_i = & \dot{V}_{i-1} + z_i\Big(z_{i+1} + \gamma(\epsilon_i + \hbar_i) + f_i(X) \\ & + g_i(\bar{x}_{i,\tau(t)}) + d_i - \dot{\gamma}\theta_{i-1} - \gamma\dot{\theta}_{i-1}\Big) - \tilde{\eta}_i\dot{\hat{\eta}}_i \\ & + \psi_i\dot{\psi}_i - \tilde{\Lambda}_i\dot{\hat{\Lambda}}_i + \dot{W}_i \\ \leq & \dot{V}_{i-1} - z_i^{2q} + \frac{1}{2}z_i^2 + \frac{1}{2}z_{i+1}^2 + z_i\gamma\epsilon_i + z_i\gamma\hbar_i \\ & + \check{z}_i\Big(F_i(X, \gamma, \dot{\gamma}, \theta_{i-1}, \dot{\theta}_{i-1}) + D_i\Big) \\ & + z_i g_i(\bar{x}_{i,\tau(t)}) - \tilde{\eta}_i\dot{\hat{\eta}}_i + \psi_i\dot{\psi}_i - \tilde{\Lambda}_i\dot{\hat{\Lambda}}_i + \dot{W}_i \\ & - 2\tanh^2\Big(\frac{z_i}{l_i}\Big)\phi_i, \end{aligned} \tag{37}$$

where $F_i(X, \gamma, \dot{\gamma}, \theta_{i-1}, \dot{\theta}_{i-1}) = \gamma\big(f_i(X) - \dot{\gamma}_i\theta_{i-1} - \gamma_i\dot{\theta}_{i-1} + z_i^{2q-1}\big) + \big(2\gamma\tanh^2(\frac{z_i}{l_i})\phi_i\big)/z_i$, with $D_i = \gamma d_i(t)$, $|D_i| \leq \Lambda_i$, and Λ_i is an unknown constant.

Following step 1, one denotes $F_i(\Delta_i) = \Xi_i^{\mathrm{T}}\Pi_i(\Delta_i)+o_i$ with $\Delta_i=(X,\gamma,\dot\gamma,\theta_{i-1},\dot\theta_{i-1})$. Since Δ_i is the attacked state and cannot be used for feedback design, one replaces Δ_i by the system state $\check\Delta_i=(\check X,\gamma,\dot\gamma,\theta_{i-1},\dot\theta_{i-1})$ and obtains the following relationship:

$$F_i(X,\gamma,\dot\gamma,\theta_{i-1},\dot\theta_{i-1}) = \Xi_i^{\mathrm{T}}\Pi_i(\check\Delta_i)+\Xi_i^{\mathrm{T}}\Big(\Pi_i(\Delta_i) - \Pi_i(\check\Delta_i)\Big)+o_i. \tag{38}$$

Using (11), one can derive

$$z_i g_i \le \frac{1}{4}z_i^2+\sum_{j=1}^{i}\Theta_{i.j}^2(x_{j,\tau(t)}). \tag{39}$$

Invoking (37)–(39) yields

$$\begin{aligned}\dot V_i \le& \dot V_{i-1}-z_i^{2q}+\frac{3}{4}z_i^2+\frac{1}{2}z_{i+1}^2+z_i\gamma\epsilon_i+z_i\gamma\hbar_i\\&+\check z_i\Big(\Xi_i^{\mathrm{T}}\Pi_i(\check\Delta_i)+D_i\Big)+\check z_i\Psi_i-b_{i1}W_i\\&-\tilde\eta_i\dot{\hat\eta}_i+\psi_i\dot\psi_i-\tilde\Lambda_i\dot{\hat\Lambda}_i+\Big(1-2\tanh^2\Big(\frac{z_i}{l_i}\Big)\Big)\phi_i,\end{aligned} \tag{40}$$

where $\Psi_i=\Xi_i^{\mathrm{T}}\Big(\Pi_i(\Delta_i)-\Pi_i(\check\Delta_i)\Big)+o_i$. Based on Assumptions 1 and 2, one can obtain $|\Psi_i|\le\bar\Psi_i$, where $\bar\Psi_i$ is a constant satisfying $\bar\Psi_i>0$. Therefore, it holds that $\check z_i\Psi_i\le c_i\check z_i^2+\frac{\bar\Psi_i^2}{4c_i}$, where c_i is a positive constant. Besides, it follows from Lemmas 1, 5, and 6 that

$$\check z_i\Big(\Xi_i^{\mathrm{T}}\Pi_i(\check\Delta_i)+D_i\Big)\le\frac{\check z_i^2\eta_i\Pi_i^{\mathrm{T}}(\check\Delta_i^*)\Pi_i(\check\Delta_i^*)}{2\delta_i^2}+\frac{\delta_i^2}{2}+\varpi_1\Lambda_i+\frac{\Lambda_i\check z_i^2}{\sqrt{\check z_i^2+\varpi_1^2}}, \tag{41}$$

where $\eta_i=||\Xi_i||^2$ and $\check\Delta_i^*=(\check x_1,\check x_2,\dots,\check x_i)$.

The adaptive laws and virtual controller are given by

$$\begin{cases}\hbar_i=-k_i\check z_i+N(\xi_i)\bar\hbar_i+\psi_i,\\ \bar\hbar_i=\dfrac{\check z_i\hat\eta_i\Pi_i^{\mathrm{T}}(\check\Delta_i^*)\Pi_i(\check\Delta_i^*)}{2\delta_i^2}+2c_i\check z_i+\dfrac{\hat\Lambda_i\check z_i}{\sqrt{\check z_i^2+\varpi_i^2}},\\ \dot{\hat\eta}_i=\dfrac{\check z_i^2\Pi_i^{\mathrm{T}}(\check\Delta_i^*)\Pi_i(\check\Delta_i^*)}{2\delta_i^2}-\rho_{i1}\hat\eta_i,\\ \dot{\hat\Lambda}_i=\dfrac{\check z_i^2}{\sqrt{\check z_i^2+\varpi_i^2}}-\rho_{i2}\hat\Lambda_i,\end{cases} \tag{42}$$

where $\dot\xi_i=\check z_i\bar\hbar_i$, and k_i, ρ_{i1}, and ρ_{i2} are some positive constants.

Substituting (18), (41), and (42) into (40) yields

$$\begin{aligned}\dot V_i\le&\dot V_{i-1}-z_i^{2q}-\bar k_iz_i^2-b_{i1}W_i+\frac{1}{2}z_{i+1}^2\\&+\Big(\bar n_i(t)N(\xi_i)+1\Big)\dot\xi_i+\rho_{i1}\tilde\eta_i\hat\eta_i\\&+\rho_{i2}\tilde\Lambda_i\hat\Lambda_i-\bar a_{1,i}\psi_i^2-a_{2,i}\psi_i^{2q}-\bar a_{3,i}\epsilon_i^2\\&+\Big(1-2\tanh^2\Big(\frac{z_i}{l_i}\Big)\Big)\phi_i+\zeta_i,\end{aligned} \tag{43}$$

where $\bar n_i(t)=\gamma^2$, $\bar k_i=k_i-\frac{3}{2}$, $\bar a_{1,i}=a_{1,i}-(\frac{1}{2}+2\gamma_{\mathrm{M}}^2)$, $\bar a_{3,i}=a_{3,i}-(\frac{1}{2}+2\gamma_{\mathrm{M}}^2)-\frac{1}{4c_i}$, $\zeta_i=\frac{\bar\Psi_i^2}{4c_i}+\frac{\delta_i^2}{2}+\varpi_1\Lambda_i$. Following the same calculation as adopted in (30)–(32) in step 1, one can obtain

$$\begin{aligned}\dot V_i\le&\sum_{j=1}^{i}\Big(-\bar k_jz_j^2-z_j^{2q}+\big(\bar n_j(t)N(\xi_j)+1\big)\dot\xi_j\\&-\bar a_{1,j}\gamma_j^2-a_{2,j}\gamma_j^{2q}-\bar a_{3,j}\epsilon_j^2+\bar\zeta_j\\&+\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j-\bar b_{j1}W_j-b_{j2}W_j^q\\&-\frac{\bar\rho_{j1}}{2}\tilde\eta_j^2-\bar\rho_{j1}\Big(\frac{1}{2}\tilde\eta_j^2\Big)^q-\frac{\bar\rho_{j1}}{2}\tilde\Lambda_j^2-\bar\rho_{j1}\Big(\frac{1}{2}\tilde\Lambda_j^2\Big)^q\Big)\\&+\frac{1}{2}z_{i+1}^2,\end{aligned} \tag{44}$$

where b_{j2} is a positive constant, $\bar b_{j1}=b_{j1}-b_{j2}>0$, and $\bar\zeta_j=\zeta_j+\bar\rho_{j1}\eta_j^2+\bar\rho_{j2}\Lambda_j^2+(\bar\rho_{j1}+\bar\rho_{j2}+b_{j2})(1-q)\varrho$.

Step n: According to (1) and (15), one calculates

$$\begin{aligned}\dot z_n=&u+f_n(X)+g_n(\bar x_{n,\tau(t)})+d_n\\&-\dot\gamma\theta_{n-1}-\gamma\dot\theta_{n-1}.\end{aligned} \tag{45}$$

The triggering event condition is described as

$$\begin{cases}u(t)=v(t_k),\forall t\in[t_k,t_{k+1}),\\ t_{k+1}=\inf\{t\in\mathbb{R}\mid|e(t)|\ge\bar k|u(t)|+m\},\end{cases} \tag{46}$$

where $e(t)=v(t)-u(t)$, and $\bar k$, m are designed parameters satisfying $0<\varphi_1k<1$, $m>0$.

With the help of (46), one has $|v(t)-u(t)|\le\bar k|u(t)|+m$, $\forall t>t_0$. If $u(t)\ge0$, it follows that

$$-\bar ku(t)-m\le v(t)-u(t)\le\bar ku(t)+m. \tag{47}$$

By (47), it is known that for some time-varying parameter $\varphi(t)$, $|\varphi(t)|\le1$, one has

$$v(t)-u(t)=\varphi(t)\big(\bar ku(t)+m\big). \tag{48}$$

If $u(t)<0$, in a similar way one has

$$v(t)-u(t)=\varphi(t)\big(\bar ku(t)-m\big). \tag{49}$$

Considering (48) and (49), one can derive

$$u(t)=\frac{v(t)}{1+\varphi_1\bar{k}}-\frac{\varphi_2 m}{1+\varphi_1\bar{k}}, \tag{50}$$

where $\varphi_1=\varphi_2=\varphi$ if $u(t)>0$, and otherwise $\varphi_1=\varphi$, $\varphi_2=-\varphi$.

From (45) and (50), it is calculated that

$$\begin{aligned}\dot{z}_n=&\frac{v}{1+\varphi_1\bar{k}}-\frac{\varphi_2 m}{1+\varphi_1\bar{k}}+f_n(X)\\&+g_n(\bar{x}_{n,\tau(t)})+d_n-\dot{\gamma}\theta_{n-1}-\gamma\dot{\theta}_{n-1}.\end{aligned} \tag{51}$$

The Lyapunov function is chosen as

$$\begin{aligned}V_n=&V_{n-1}+\frac{1}{2}z_n^2+\frac{1}{2}\tilde{\eta}_n^2+\frac{1}{2}\psi_n^2\\&+\frac{1}{2}\tilde{\varLambda}_n^2+\frac{1}{2}\tilde{\chi}^2+W_n,\end{aligned} \tag{52}$$

where $W_n=\sum_{j=1}^{n}\left(\mathrm{e}^{b_{n1}\overline{\tau}_j}/(1-\overline{\tau}_{j\mathrm{d}})\right)\mathrm{e}^{-b_{n1}t}\int_{t-\tau_j(t)}^{t}\mathrm{e}^{b_{n1}s}\varTheta_{n.j}^2\big(x_j(s)\big)\mathrm{d}s$, b_{n1} is a positive constant, and $\tilde{\chi}=\chi-\hat{\chi}$, $\chi=c_n\gamma_{\mathrm{M}}^4$. From (51), one can obtain

$$\begin{aligned}\dot{V}_n\le&\dot{V}_{n-1}-z_n^{2q}+z_n\Big(\frac{v}{1+\varphi_1\bar{k}}-\frac{\varphi_2 m}{1+\varphi_1\bar{k}}+\gamma\hbar_n\\&-\gamma\hbar_n\Big)+z_n g_n(\bar{x}_{n,\tau(t)})-2\tanh^2\left(\frac{z_n}{l_n}\right)\phi_n\\&+\check{z}_n\Big(F_n(X,\gamma,\dot{\gamma},\theta_{n-1},\dot{\theta}_{n-1})+D_n\Big)\\&-\tilde{\chi}\dot{\hat{\chi}}-\tilde{\eta}_n\dot{\hat{\eta}}_n+\psi_n\dot{\psi}_n-\tilde{\varLambda}_n\dot{\hat{\varLambda}}_n+\dot{W}_n,\end{aligned} \tag{53}$$

where $F_n(X,\gamma,\dot{\gamma},\theta_{n-1},\dot{\theta}_{n-1})=\gamma\big(f_n(X)-\dot{\gamma}_n\theta_{n-1}-\gamma_n\dot{\theta}_{n-1}+z_n^{2q-1}\big)+\big(2\gamma\tanh^2(\frac{z_n}{l_n})\phi_n\big)/z_n$, $\phi_n=\sum_{j=1}^{n}\frac{\mathrm{e}^{b_{n1}\overline{\tau}_j}}{1-\overline{\tau}_{j\mathrm{d}}}\varTheta_{n.j}^2\big(x_j(t)\big)$, $D_n=\gamma d_n(t)$ with $|D_n|\le\varLambda_n$, and $\varLambda_n$ is an unknown constant.

Following the previous step, one denotes $F_n(X,\gamma,\dot{\gamma},\theta_{n-1},\dot{\theta}_{n-1})=\varXi_n^{\mathrm{T}}\varPi_n(\varDelta_n)+o_n$ with $\varDelta_n=(X,\gamma,\dot{\gamma},\theta_{n-1},\dot{\theta}_{n-1})$. Following the definition of W_n above, one can obtain the derivative of W_n as

$$\dot{W}_n\le-b_{n1}W_1+\phi_n-\sum_{j=1}^{n}\varTheta_{n.j}^2(x_{j,\tau(t)}). \tag{54}$$

Using (11), one can derive

$$z_n g_n\le\frac{1}{4}z_n^2+\sum_{j=1}^{n}\varTheta_{n.j}^2(x_{j,\tau(t)}). \tag{55}$$

Invoking (53)–(55) yields

$$\begin{aligned}\dot{V}_n\le&\dot{V}_{n-1}-z_n^{2q}+\frac{1}{4}z_n^2-b_{n1}W_n\\&+z_n\Big(\frac{v}{1+\varphi_1\bar{k}}-\frac{\varphi_2 m}{1+\varphi_1\bar{k}}+\gamma\hbar_n-\gamma\hbar_n\Big)\\&+\check{z}_n\varPsi_n+\check{z}_n\Big(\varXi_n^{\mathrm{T}}\varPi_n(\check{\varDelta}_n)+D_n\Big)\\&+\Big(1-2\tanh^2\left(\frac{z_n}{l_n}\right)\Big)\phi_n\\&-\tilde{\eta}_n\dot{\hat{\eta}}_n+\psi_n\dot{\psi}_n-\tilde{\varLambda}_n\dot{\hat{\varLambda}}_n-\tilde{\chi}\dot{\hat{\chi}},\end{aligned} \tag{56}$$

where $\varPsi_n=\varXi_n^{\mathrm{T}}\Big(\varPi_n(\varDelta_n)-\varPi_n(\check{\varDelta}_n)\Big)+o_n$. Similarly, one can obtain $|\varPsi_n|\le\bar{\varPsi}_n$, where $\bar{\varPsi}_n$ is a constant satisfying $\bar{\varPsi}_n>0$. Therefore, it holds that $\check{z}_n\varPsi_n\le c_n\check{z}_n^2+\frac{\bar{\varPsi}_n^2}{4c_n}$. Using Lemmas 1, 5, and 6, one has the following estimation:

$$\begin{aligned}&\check{z}_n\Big(\varXi_n^{\mathrm{T}}\varPi_n(\check{\varDelta}_n)+D_n\Big)\\&\le\frac{\check{z}_n^2\eta_n\varPi_n^{\mathrm{T}}(\check{\varDelta}_n^*)\varPi_n(\check{\varDelta}_n^*)}{2\delta_n^2}\\&\quad+\frac{\delta_n^2}{2}+\varpi_1\varLambda_n+\frac{\varLambda_n\check{z}_n^2}{\sqrt{\check{z}_n^2+\varpi_1^2}},\end{aligned} \tag{57}$$

where $\eta_n=||\varXi_n||^2$ and $\check{\varDelta}_n^*=(\check{x}_1,\check{x}_2,\ldots,\check{x}_n)$. To deal with the term $\frac{\varphi_2 m}{1+\varphi_1\bar{k}}$ in (56), one derives

$$-\frac{z_n\varphi_2 m}{1+\varphi_1\bar{k}}\le\Big|\frac{z_n\varphi_2 m}{1+\varphi_1\bar{k}}\Big|\le\frac{1}{4}z_n^2+\Big(\frac{m}{1-\bar{k}}\Big)^2. \tag{58}$$

The adaptive laws and virtual controller are given by

$$\begin{cases}\hbar_n=-k_n\check{z}_n+N(\xi_n)\bar{\hbar}_n+\psi_n,\\ \bar{\hbar}_n=\dfrac{\check{z}_n\hat{\eta}_n\varPi_n^{\mathrm{T}}(\check{\varDelta}_n^*)\varPi_n(\check{\varDelta}_n^*)}{2\delta_n^2}+c_n\check{z}_n+\dfrac{\hat{\varLambda}_n\check{z}_n}{\sqrt{\check{z}_n^2+\varpi_n^2}},\\ \dot{\hat{\eta}}_n=\dfrac{\check{z}_n^2\varPi_n^{\mathrm{T}}(\check{\varDelta}_n^*)\varPi_n(\check{\varDelta}_n^*)}{2\delta_n^2}-\rho_{n1}\hat{\eta}_n,\\ \dot{\hat{\varLambda}}_n=\dfrac{\check{z}_n^2}{\sqrt{\check{z}_n^2+\varpi_n^2}}-\rho_{n2}\hat{\varLambda}_n,\end{cases} \tag{59}$$

where $\dot{\xi}_n=\check{z}_n\bar{\hbar}_n$, and k_n, ρ_{n1}, and ρ_{n2} are positive constants.

Substituting (18) and (57)–(59) into (56) yields

$$\begin{aligned}\dot{V}_n \leq& \dot{V}_{n-1} - z_n^{2q} - \bar{k}_n z_n^2 - b_{n1}W_n \\ &+ \Big(\bar{n}_n(t)N(\xi_n)+1\Big)\dot{\xi}_n + z_n\Big(\frac{v}{1+\varphi_1\bar{k}} - \gamma\hbar_n\Big) \\ &+ \Big(1-2\tanh^2\Big(\frac{z_n}{l_n}\Big)\Big)\varPsi_n - \bar{a}_{1,n}\psi_n^2 - a_{2,n}\psi_n^{2q} \\ &- \bar{b}_{n1}W_n - b_{n2}W_n^q - \frac{\bar{\rho}_{n1}}{2}\tilde{\eta}_n^2 - \frac{\bar{\rho}_{n1}}{2}\tilde{\eta}_n^{2q} \\ &- \frac{\bar{\rho}_{n2}}{2}\tilde{\varLambda}_n^2 - \frac{\bar{\rho}_{n2}}{2}\tilde{\varLambda}_n^{2q} - \tilde{\chi}\dot{\hat{\chi}} + \zeta_n,\end{aligned} \tag{60}$$

where $\bar{n}_n(t)=\gamma^2$, $\bar{k}_n = k_n - \frac{3}{4}$, $\bar{a}_{1,n} = a_{1,n} - \gamma_M^2$, $\zeta_n = \frac{\bar{\psi}_n^2}{4c_n} + \frac{\delta_n^2}{2} + \varpi_1\varLambda_n + (\frac{m}{1-k})^2$.

The adaptive laws and virtual controller are given by

$$\begin{cases} v = N(\xi_{n+1})\bar{\hbar}_{n+1}, \\ \bar{\hbar}_{n+1} = \check{z}_n\hat{\chi}\hbar_n^2, \\ \dot{\hat{\chi}} = \check{z}_n^2\hbar_n^2 - \rho_{(n+1)1}\hat{\chi}, \end{cases} \tag{61}$$

where $\dot{\xi}_{n+1} = \check{z}_n\bar{\hbar}_{n+1}$. Substituting (61) into (60), we obtain

$$\begin{aligned}\dot{V}_n \leq& \sum_{j=1}^{n}\Big(-\bar{k}_j z_j^2 - z_j^{2q} - \bar{a}_{1.j}\gamma_j^2 - a_{2.j}\gamma_j^{2q} \\ &+ \Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j + \bar{\zeta}_j - \bar{b}_{j1}W_j - b_{j2}W_j^q \\ &- \frac{\bar{\rho}_{j1}}{2}\tilde{\eta}_j^2 - \bar{\rho}_{j1}\Big(\frac{1}{2}\tilde{\eta}_j^2\Big)^q - \frac{\bar{\rho}_{j1}}{2}\tilde{\varLambda}_j^2 - \bar{\rho}_{j1}\Big(\frac{1}{2}\tilde{\varLambda}_j^2\Big)^q\Big) \\ &- \sum_{j=1}^{n-1}\bar{a}_{3.j}\epsilon_j^2 + \sum_{j=1}^{n+1}\Big(\bar{n}_j(t)N(\xi_j)+1\Big)\dot{\xi}_j \\ &- \frac{\bar{\rho}_{(n+1)1}}{2}\tilde{\chi}^2 - \bar{\rho}_{(n+1)1}\Big(\frac{1}{2}\tilde{\chi}^2\Big)^q,\end{aligned} \tag{62}$$

where $\bar{\zeta}_n = \zeta_n + \bar{\rho}_{(n+1)1}\chi^2 + \bar{\rho}_{(n+1)1}(1-q)\varrho + \frac{1}{4c_n}$.

By selecting the design parameters, (62) can be expressed as

$$\begin{aligned}\dot{V}_n \leq& -\mu_1 V_n - \mu_2 V_n^q + \sum_{j=1}^{n+1}\Big(\bar{n}_j(t)N(\xi_j)+1\Big)\dot{\xi}_j \\ &+ \sum_{j=1}^{n}\Big(\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j + \bar{\zeta}_j\Big),\end{aligned} \tag{63}$$

where $\mu_1 = \min\{2\bar{k}_j, 2\bar{a}_{1.j}, \bar{\rho}_{m1}, \bar{\rho}_{m2}, \bar{b}_{j1}\}$, $\mu_2 = \min\{2^q, 2^q a_{2.j}, \bar{\rho}_{m1}, \bar{\rho}_{m2}, b_{j2}\}$, $m = 1,2,...,n+1$, $j = 1,2,...,n$.

Now, we can summarize the main result.

Theorem 1 Consider the nonlinear time-delay CPS (1) with deception attacks (2). The control law (61), including the event-triggered mechanism (46), the FO filter (17), and the adaptive laws (28), (42), and (59) can guarantee that:

(1) All signals of the closed-loop systems are practically finite-time stable.

(2) The tracking error converges to a small neighborhood of the origin within time T_f as

$$\begin{aligned}T_\mathrm{f} \leq \max\Big\{&\frac{1}{a\mu_1(1-q)}\ln\frac{a\mu_1 V_n^{1-q}(0)+\mu_2}{\mu_2}, \\ &\frac{1}{\mu_1(1-q)}\ln\frac{\mu_1 V_n^{1-q}(0)+a\mu_2}{a\mu_2}\Big\}.\end{aligned} \tag{64}$$

Proof The term $\sum_{j=1}^{n}\Big(1-2\tanh^2(\frac{z_j}{l_j})\Big)\phi_j$ in (63) can be rewritten as

$$\begin{aligned}&\sum_{j=1}^{n}\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j \\ &= \sum_{z_i\in\varPi_{z_i}}\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j \\ &\quad + \sum_{z_i\notin\varPi_{z_i}}\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j.\end{aligned} \tag{65}$$

With the help of Lemma 3 in Ge SS and Tee (2007), it follows from (63) and (65) that

$$\dot{V}_n \leq -\mu_1 V_n - \mu_2 V_n^q + \sum_{j=1}^{n+1}\Big(\bar{n}_j(t)N(\xi_j)+1\Big)\dot{\xi}_j + \mu_3, \tag{66}$$

where the parameter μ_3 satisfies $|\sum_{j=1}^{n}\bar{\zeta}_j + \varkappa_1 + \varkappa_2| < \mu_3$ with $\varkappa_1 = \sum_{z_i\in\varPi_{z_i}}\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j$ and $\varkappa_2 = \sum_{z_i\notin\varPi_{z_i}}\Big(1-2\tanh^2\Big(\frac{z_j}{l_j}\Big)\Big)\phi_j$.

Recalling Lemma 2, one knows that $\sum_{j=1}^{n+1}\Big(\bar{n}_j(t)N(\xi_j)+1\Big)\dot{\xi}_j$ is bounded over the interval $[0,t_\mathrm{s})$. By defining $\mu_{\max} = \max_{t\in[0,t_\mathrm{s})}\sum_{j=1}^{n+1}\Big(\bar{n}_j(t)N(\xi_j)+1\Big)\dot{\xi}_j$, and $\mu_\mathrm{M} = \mu_3 + \mu_{\max}$, (66) becomes

$$\dot{V}_n \leq -\mu_1 V_n - \mu_2 V_n^q + \mu_\mathrm{M}. \tag{67}$$

The inequality above implies that all signals of the closed-loop system are practically finite-time stable.

On the other hand, by using (67), it can be deduced that

$$\lim_{t\to T_\mathrm{f}} V_n \leq \min\Big\{\frac{\mu_\mathrm{M}}{(1-a)\mu_1}, \Big(\frac{\mu_\mathrm{M}}{(1-a)\mu_2}\Big)^{\frac{1}{q}}\Big\}, \tag{68}$$

where a satisfies $0 < a < 1$ and

$$T_{\mathrm{f}} \leq \max\left\{\frac{1}{a\mu_1(1-q)}\ln\frac{a\mu_1 V_n^{1-q}(0)+\mu_2}{\mu_2},\right.$$
$$\left.\frac{1}{\mu_1(1-q)}\ln\frac{\mu_1 V_n^{1-q}(0)+a\mu_2}{a\mu_2}\right\}. \quad (69)$$

Considering the definition of V_n, it is deduced that

$$|z_1| \leq \min\left\{\sqrt{\frac{2\mu_{\mathrm{M}}}{(1-a)\mu_1}}, \sqrt{2\left(\frac{\mu_{\mathrm{M}}}{(1-a)\mu_2}\right)^{\frac{1}{q}}}\right\}, \quad (70)$$

with the finite time T_{f}. Therefore, the tracking error eventually tends to a small region of the origin in a finite time T_{f}.

Remark 4 In Song et al. (2022b), FO command filtering was introduced to achieve finite-time boundedness of closed-loop signals. In our context, by considering both the reference signal and the attack gains, the finite-time tracking task is guaranteed. Compared with the tracking result (Chen WD et al., 2022), the coordinate transformation is embedded into fractional-order command filtering to obtain the virtual control law and overcome the complexity explosion issue. Apart from this point, unlike the approach adopted in Chen WD et al. (2022) and Song et al. (2022b), the proposed method is suitable for more general CPSs with time-delay and non-strict feedback structures.

4 Simulations

This section demonstrates the effectiveness of the designed method for the chemical reactor system (Song et al., 2022b). By considering time delays, the model dynamics are given as

$$\begin{cases} \dot{x}_1(t) = \iota_1 x_2(t) + \iota_2 x_1(t) + x_1(t-\tau), \\ \dot{x}_2(t) = \iota_3 u(t) - \iota_4 x_2(t) - \iota_5 x_2^2(t) - x_2(t-\tau), \end{cases} \quad (71)$$

where the values of the parameters ι_i ($i = 1, 2, 3, 4, 5$) can be taken from Song et al. (2022b).

The event-triggered command-filtered tracking control scheme can be obtained using the design process elucidated in Section 3. In the example, a comparison is proposed with the result achieved in Song et al. (2022b) without considering the tracking task. We choose the attacks $\lambda_i = (-0.3 - 0.25\sin t)x_i$, $i = 1, 2, 3$, and the tracking reference $y_{\mathrm{d}} = 0.1\sin(2\pi t)$. $k_1 = 5$, $k_2 = 3.5$, $c_1 = 0.005$, $c_2 = 0.01$, $\rho_{i,j} = 2$, $i = 1, 2$, $j = 1, 2$, $\alpha_{1,1} = \alpha_{1,2} = 2$, $\alpha = 0.9$, $x_1(0) = 1$, $x_2(0) = 1.4$, and the other initial values are zero.

Figs. 1–6 show the example results. Fig. 1 shows the tracking error under the proposed method and Song et al. (2022b)'s method. In Song et al. (2022b), the classical coordinate conversion was constructed without considering tracking control. Fig. 1 shows that the proposed method guarantees a good finite-time tracking behavior with a smaller tracking error than that in Song et al. (2022b). Fig. 2 indicates the system states bounded in a finite time. Figs. 3 and 4 show the adaptive laws that offset the influences of the uncertain functions and attack signals. Fig. 5 depicts the evolution of the parameter variables in Nussbaum-type functions, which are used to handle the time-delay attack weight. It is clear that these variables are all bounded. Fig. 6 presents the control input efforts, and the proposed method can greatly save communication resources.

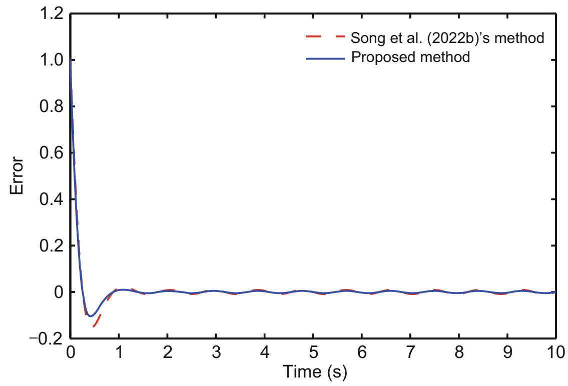

Fig. 1 Tracking error

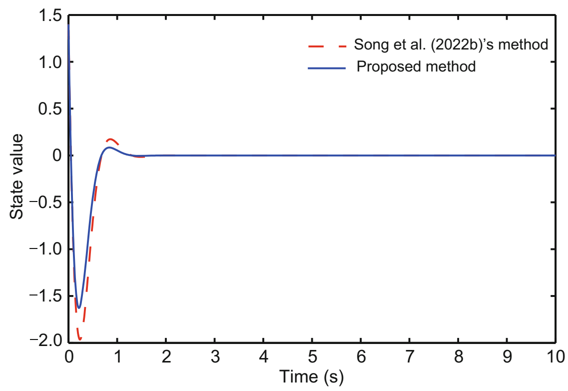

Fig. 2 System state x_2

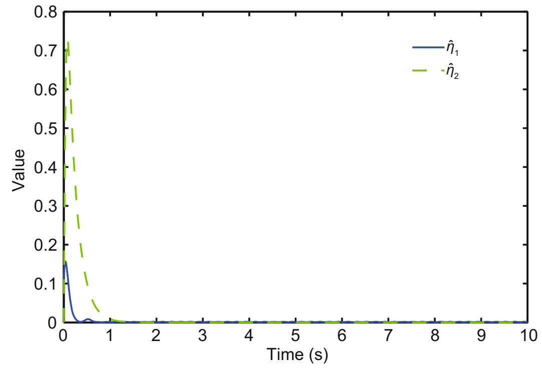

Fig. 3 Adaptive laws $\hat{\eta}_1$ and $\hat{\eta}_2$

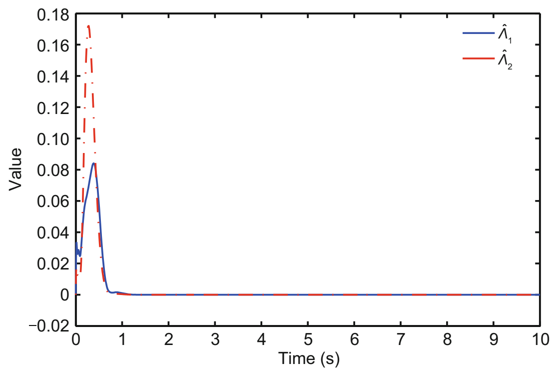

Fig. 4 Adaptive laws $\hat{\Lambda}_1$ and $\hat{\Lambda}_2$

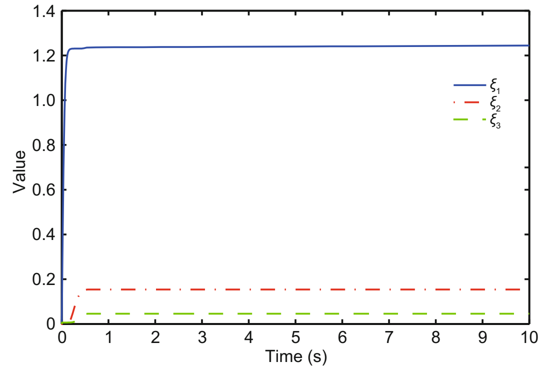

Fig. 5 Parameter variables ξ_1, ξ_2, and ξ_3

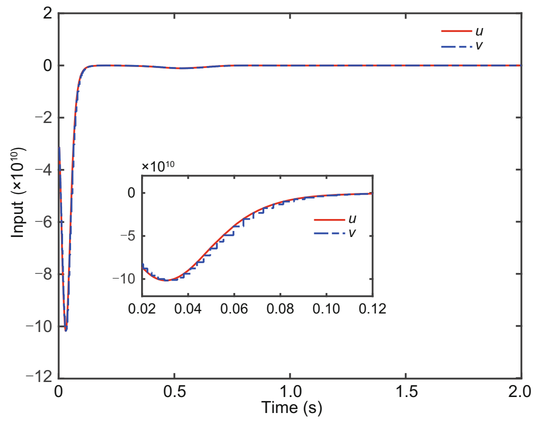

Fig. 6 Inputs u and v

5 Conclusions

This article has addressed the problem of finite-time tracking control for the event-triggered nonlinear time-delayed CPSs with deception attacks. A new coordinate conversion technique is proposed to deal with the influence of attack gain. The modified FOCF backstepping recursive process and the Nussbaum gain function are introduced to address the complexity explosion issue and deal with the time-varying weight. In future research, the proposed scheme can be extended to a class of CPSs with mismatched disturbance and a stochastic phenomenon.

Contributors

Yajing MA and Zhanjie LI designed the research. Yajing MA and Yuan WANG processed the data. Yajing MA and Zhanjie LI drafted the paper. Yuan WANG helped organize the paper. Zhanjie LI and Xiangpeng XIE revised and finalized the paper.

Compliance with ethics guidelines

Yajing MA, Yuan WANG, Zhanjie LI, and Xiangpeng XIE declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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