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Research article

Decentralized observer-based event-triggered control for an interconnected fractional-order system with stochastic Cyber-attacks

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Abstract: The problem of decentralized observer-based event-triggered stabilization for an interconnected fractional-order system subject to stochastic cyber-attacks is studied. To address this issue, the decentralized event-triggered mechanism is proposed for the interconnected fractional-order system, where the event-triggered schemes are designed based on the states of fractional-order observers, and the stochastic attacks are considered both on control inputs and observer outputs. By combining decentralized observers and decentralized event-triggered controllers, we aim to achieve decentralized control with reduced amplifying error and use local signals to improve overall system performance. By utilizing the diffusive representation of the fractional-order system, the interconnected fractional-order system is transformed into an equivalent integer-order one to simplify the analysis and control design. Employing the Lyapunov indirect approach, a sufficient condition is obtained to guarantee the stochastic asymptotically stability of the augmented system. Additionally, by the singular value decomposition technique, the approach of simultaneously computing the decentralized observer gains and controller gains is presented. Finally, a simulation example is provided to validate the theoretical findings.

Keywords: interconnected fractional-order system; event-triggered control; observer; stochastic cyber-attack; Lyapunov indirect approach
Mathematics Subject Classification: 93A14, 93B50, 93D99

1. Introduction

Fractional-order systems (FOS) have received considerable attention and application due to many engineering and physical systems can be characterized by it quite precisely [1], such as quantum mechanics systems [2], financial systems [3], fluid mechanics systems [4], reaction-diffusion systems [5], biological systems [6] and so on. As with the integer-order systems, the stability of FOSs is also developed by the Lyapunov method in some works [7,8]. On the other hand, considering the history-dependent properties of fractional-order integral and differential, fractional-order controllers show clear advantages and are designed for FOSs and integer-order systems (IOSs) [9–11].

An interconnected system consists of several coupled subsystems, such as power systems [12] and vehicular systems [13], that are modeled as interconnected systems to illustrate the information exchange of subsystems. In an interconnected system, if the subsystems are all described with fractional-order differential equations, it is an interconnected fractional-order system (IFOS). Due to the interconnection characteristic and the fractional-order feature, the analysis and synthesis of IFOSs would be much more complex. The robust decentralized control problem for a perturbed IFOS was studied in [14]. In [15], the stability analysis and functional observer design for a linear IFOS was investigated. Nithya et al. [16] designed the decentralized resilient controller for an IFOS with uncertainty. In [15] and [16], the diffusive representation of the FOS was utilized and then given the results by transforming FOSs to be IOSs. Chen et al. [17] focused on the finite-time boundness of a linear IFOS subject to input saturation. By introducing a neural network observer, Li et al. [18] designed a decentralized fault-tolerant controller for a nonlinear IFOS. Yu et al. [19] proposed a decentralized periodic intermittent control method for IFOS by a part of variables. The stability criteria are derived, while the stabilization problem is unsettled. From the limited results, the stability and stabilization of IFOS have not been fully investigated.

To reduce the communication burden, event-triggered mechanisms (ETM) are proposed for control systems. Event-triggered control (ETC) is prescribed that control signals be transmitted to the systems only when the pre-defined ETM is satisfied [20]. Thus, as a prerequisite, the performance of the system is guaranteed, and the communication resources can be saved. Over the past few years, various ETMs have been developed for interconnected systems [21,22], such as the static ETM [23], the state-dependent ETM [24], the time-dependent ETM [25], the Lyapunov-based ETM [26], the Model-based ETM [27], and the Parsimonious ETM [28].

In the practical plants, not all the internal states are available. It is proposed that the observer-based state feedback controller utilize the estimated states to control the inputs and enable the closed-loop system stable. Therefore, combined with ETM, observer-based event-triggered control is an effective and practical way to control a system. An event-triggered strategy with a neural-network pattern was proposed to investigate the problem of sliding mode control for uncertain differential algebraic systems [29]. The observer-based event-triggered stabilization of perturbed singular systems was studied in [30]. In [31], the observer-based robust control problem for singular switched FOSs with actuator saturation was studied. The observer-based event-triggered control for uncertain linear FOSs was investigated in [32]. In [33], Stochastic network attacks were considered in an uncertain fractional-order system, and the observer and event-triggered scheme are designed to investigate the output feedback control problem. On the other hand, for interconnected systems, the subsystems are usually located at a remote distance, thus the decentralized control scheme is an efficient pattern due to only the local information being required to control the local subsystem. However, the decentralized observer-based event-triggered control problems for IFOS have not yet received enough attention.

The security control problem is an utmost important issue that has attracted researchers to focus on it. In practical control systems, cyber-attacks occur frequently due to control components such as sensors, controllers and actuators being connected via a shared communication network. In the existing works, deception attacks, Denial-of-service (DoS) attacks, replay attacks and integrity attacks have been discussed. In [34] and [35], the security control problems of the networked control systems under deception attacks were investigated. Ding et al. [36] considered the deception attacks on a nonlinear system. Foroush et al. [37] considered Denial-of-service (DoS) attacks on linear systems. Zhu et al. [38] investigated the resilient networked control systems subject to replay attacks. Mo et al. [39] focused on the linear time-invariant system subject to integrity attacks. Nevertheless, fewer works on the synchronization of the FOS subject to cyber-attacks have been reported due to the complexity of the stochastic nature of attacks and the fractional differentiation [33].

Motivated by the aforementioned discussions, we focus on addressing the decentralized observer-based event-triggering stabilization problems for an interconnected fractional-order system. We construct a group of decentralized fractional-order observers, and a group of decentralized event-triggered controllers with local observer feedback signals to trigger control updates. By combining decentralized observers and event-triggered controllers, the proposed approach aims to achieve decentralized control with reduced amplifying error and improved overall system performance. Our major contributions are: (i) Through the diffusive representation of FOS and multi-Lyapunov function, the sufficient condition of stochastical stability of IFOS is first derived. (ii) The stochastic cyber-attacks are considered both on the controller inputs and the observer outputs. (iii) The decentralized Observer-based Event-triggered Control framework is constructed, subsequently, the stabilization problem is solved, enabling the simultaneous calculation of the controller gains and observer gains.

Notations: For a given matrix X with appropriate dimension, X^T is the transpose of X and X^{-1} is the inverse of X. $X > 0$ ($X < 0$) denotes that the matrix X is positive definite (negative definite). The asterisk "*" denotes the symmetric terms in the matrix. $\mathbf{R}^n$ is the set of the n-dimensional real vectors, and $\mathbf{R}^{m\times n}$ is the set of $m \times n$ real matrices. The set $N[1,n] \triangleq \{1,2,\cdots,n\}$, and the set $\aleph_i \triangleq N[1,n]\backslash\{i\}$, where $n > 1$ is an integer. For a vector $x = (x_1, x_2, \cdots, x_m)$, $\|x\|$ is the Euclidean norm, and $\|x\| = \sqrt{\sum_{i=1}^{m} x_i^2}$. $\mathcal{L}V(t)$ represents the weak infinitesimal operator of function $V(t)$. $\mathbf{E}\{\cdot\}$ stands for the mathematical expectation.

2. Problem formulation and preliminaries

In the following, the definition of Caputo fractional-order derivative, and the model of considered IFOS are presented. In the IFOS, the fractional order $0 < \alpha < 1$.

Definition 2.1. ([1]) The Caputo fractional-order derivative with order α of function $f(t)$ is defined:

$$D^{\alpha} f(t) = \frac{1}{\Gamma(\alpha-m)} \int_0^t \frac{f^{(m)}(\tau)}{(t-\tau)^{\alpha+1-m}} \mathrm{d}\tau,$$

where, $m = \lfloor\alpha\rfloor + 1$, $\lfloor\alpha\rfloor$ signifies the integer part of α; $\Gamma(\cdot)$ is the Gamma function with the definition of $\Gamma(z) = \int_0^{\infty} t^{z-1} e^{-t} dt$.

The considered IFOS coupled with n subsystems, of which the i^{th} subsystem is

$$D^{\alpha}x_i(t) = A_i x_i(t) + \sum_{j\in\aleph_i} G_{ij} g_{ij}\left(x_i(t), x_j(t)\right) + B_i u_i(t), \tag{1a}$$

$$y_i(t) = C_i x_i(t), \tag{1b}$$

where $i \in N[1, n]$. For the i^{th} subsystem, $x_i(t) = [x_{i1}(t) \quad x_{i2}(t) \cdots \quad x_{in_i}(t)]^T \in \mathbf{R}^{n_i}$ is the state vector; $y_i(t) = [y_{i1}(t) \quad y_{i2}(t) \cdots \quad y_{im_i}(t)] \in \mathbf{R}^{m_i}$ is the measured output; the actual control input is $u_i(t) = [u_{i1}(t) \quad u_{i2}(t) \cdots \quad u_{ip_i}(t)]^T \in \mathbf{R}^{p_i}$; $\sum_{j\in\aleph_i} G_{ij}\, g_{ij}\left(x_i(t), x_j(t)\right)$ are the coupled terms, which reveal the i^{th} subsystem exchanging information with neighbor subsystems; $A_i \in \mathbf{R}^{n_i\times n_i}$, $B_i \in \mathbf{R}^{n_i\times p_i}$, $C_i \in \mathbf{R}^{m_i\times n_i}$, and $G_{ij} \in \mathbf{R}^{n_i}$ are known system parameters. In this paper, the nonlinear function $g_{ij}\left(x_i(t), x_j(t)\right)$ is supposed to satisfy the quadratic inequality

$$\left\| g_{ij}\left(x_i(t), x_j(t)\right)\right\|^2 \le \|M_i x_i(t)\|^2 + \left\|M_{ij} x_j(t)\right\|^2, \tag{2}$$

where M_i and M_{ij} are known matrices.

In the view of decentralized control, the observer of the i^{th} subsystem is designed by

$$D^{\alpha}\hat{x}_i(t) = A_i\hat{x}_i(t) + L_i\left(y_i(t) - \hat{y}_i(t)\right) + B_i u_i(t), \tag{3a}$$

$$\hat{y}_i(t) = C_i\left(\hat{x}_i(t) + \beta_i(t) h_i\left(\hat{x}_i(t)\right)\right), \tag{3b}$$

$$u_i(t) = \tilde{u}_i(t) + \gamma_i(t) f_i\left(\tilde{u}_i(t)\right), \tag{3c}$$

where $i \in N[1, n]$. For the observer of the i^{th} subsystem, $\hat{x}_i(t) \in \mathbf{R}^{n_i}$ is the state; $\hat{y}_i(t) \in \mathbf{R}^{m_i}$ is the measured output vector; $L_i \in \mathbf{R}^{n_i\times m_i}$ is observer gain to be determined; Random variable $\beta_i(t)$ has the Bernoulli distribution, and $\mathbf{E}\{\beta_i(t)\} = \bar{\beta}_i$. The nonlinear function $h_i(\hat{x}_i(t))$ describes the attack on the observer system. The actual input $u_i(t)$ consists of the control input $\tilde{u}_i(t)$ and network attack $\gamma_i(t) f_i\left(\tilde{u}_i(t)\right)$. Random variable $\gamma_i(t)$ has the Bernoulli distribution, and $\mathbf{E}\{\gamma_i(t)\} = \bar{\gamma}_i$. The nonlinear function $f_i\left(\tilde{u}_i(t)\right)$ describes the attack which relating to the control input $\tilde{u}_i(t)$. It is supposed that the random variables $\beta_1(t)$, $\beta_2(t)$, $\cdots$, $\beta_n(t)$, $\gamma_1(t)$, $\gamma_2(t)$, $\cdots$, $\gamma_n(t)$ are independent.

On the other hand, considering the attacks are not measurable but bounded, to analyze the impact of these attacks on the system, certain assumptions are made. It is assumed that the attackers have knowledge about the system, including its dynamic model, control structure and observer. For the i^{th} subsystem, the attacks are supposed to satisfy the following conditions. These assumptions help in formulating the problem and developing suitable strategies to mitigate the effects of the attacks.

Assumption 1. The attack $h_i\left(\hat{x}_i(t)\right)$ satisfies

$$\left\|h_i\left(\hat{x}_i(t)\right)\right\|^2 \le \|H_i\hat{x}_i(t)\|^2, \tag{4}$$

where $H_i \in \mathbf{R}^{n_i \times n_i}$ $(i \in N[1,n])$ are known matrices. (4) representing the boundness of the attacks on the observer subsystems.

Assumption 2. The attack $f_i(\tilde{u}_i(t))$ satisfies

$$\left\|f_i(\tilde{u}_i(t))\right\|^2 \le \|F_i\tilde{u}_i(t)\|^2, \tag{5}$$

where $F_i \in \mathbf{R}$ $(i \in N[1,n])$ are known constants. (5) representing the boundness of the attacks on the control inputs.

Remark 2.1. In system (3), the independent stochastic attacks are considered both on control inputs and observer outputs. The random feature of attacks is governed by the Bernoulli process. $\beta_i(t) = 0$ means the observer outputs of the i^{th} subsystem did not under the attacks. When $\beta_i(t) = 1$, the measured observer outputs be attacked. $\gamma_i(t) = 0$ means the control inputs $\tilde{u}_i(t)$ of the i^{th} subsystem are the actual inputs $u_i(t)$. When $\gamma_i(t) = 1$, the actual inputs are $u_i(t) = \tilde{u}_i(t) + f_i(\tilde{u}_i(t))$.

For the i^{th} subsystem, we design the following decentralized observer-based event-triggered control law

$$\tilde{u}_i(t) = -K_i\hat{x}_i(t_k^i), t \in [t_k^i, t_{k+1}^i), \tag{6}$$

where $i \in N[1,n]$, $K_i \in \mathbf{R}^{p_i \times n_i}$ are controller gain matrices to be determined. t_k^i is the instant of the k^{th} event-triggering, and $\hat{x}_i(t_k^i)$ is the latest sampled observer state at the instant t_k^i of the i^{th} subsystem. The decentralized independent event-triggered mechanism is presented in (7).

$$t_{k+1}^i = \inf\left\{t \ge t_k^i + T \mid \left\|\hat{x}_i(t) - \hat{x}_i(t_k^i)\right\|^2 \ge \delta_i\|\hat{x}_i(t)\|^2\right\}, \tag{7}$$

where $i \in N[1,n]$; $\delta_i > 0$ is the threshold constant; $T > 0$ is the minimal dwell time, which guarantees the next sampling time will process at least T time units later. Furthermore, $T > 0$ prevents the Zeno phenomenon.

Remark 2.2. In addition to saving some computational and communication resources, the event-triggered mechanisms can help restrict the amplifying error by adjusting control updates based on the magnitude of the error. As we can see from (6) and (7), when the error exceeds a certain threshold or the system requires significant changes in control, an event is triggered to update the control signal. This adaptive behavior helps prevent unnecessary control updates and reduces the amplifying effect, leading to improved control performance and stability.

Based on the ETC in (6), the closed-loop system of (1) can be written as

$$D^{\alpha}x_i(t) = A_ix_i(t) + \sum_{j\in\aleph_i} G_{ij}g_{ij}\left(x_i(t), x_j(t)\right) - B_iK_i\hat{x}_i(t_k^i) + \gamma_i(t)B_if_i(\tilde{u}_i(t)). \tag{8}$$

Denote $e_i(t) \triangleq x_i(t) - \hat{x}_i(t)$, which is the estimation error, and denote

$$\hat{e}_i(t) \triangleq \hat{x}_i(t) - \hat{x}_i(t_k^i), \tag{9}$$

then the closed-loop observation system can be described as

$$D^{\alpha}\hat{x}_i(t) = (A_i - B_iK_i)\hat{x}_i(t) + B_iK_i\hat{e}_i(t) + L_iC_ie_i(t) - \beta_i(t)L_iC_ih_i(\hat{x}_i(t)) + \gamma_i(t)B_if_i(\tilde{u}_i(t)). \quad (10)$$

The dynamics of $e_i(t)$ can be written as

$$D^{\alpha}e_i(t) = (A_i - L_iC_i)e_i(t) + \sum_{j\in\aleph_i} G_{ij}g_{ij}\left(x_i(t), x_j(t)\right) + \beta_i(t)L_iC_ih_i(\hat{x}_i(t)). \quad (11)$$

Let $\chi_i(t) = [\hat{x}_i^T(t) \quad e_i^T(t)]^T$, then the augmented system can be written as

$$D^{\alpha}\chi_i(t) = \tilde{A}_i\chi_i(t) + \sum_{j\in\aleph_i} \tilde{G}_{ij}\tilde{g}_{ij}\left(\chi_i(t), \chi_j(t)\right) + \tilde{B}_i\hat{e}_i(t) + \beta_i(t)\Gamma_ih_i(\hat{x}_i(t))$$

$$+\gamma_i(t)\bar{B}_if_i(\tilde{u}_i(t)), \quad (12)$$

where $\tilde{A}_i = \begin{bmatrix} A_i - B_iK_i & L_iC_i \\ 0 & A_i - L_iC_i \end{bmatrix}$, $\tilde{G}_{ij} = \begin{bmatrix} 0 \\ G_{ij} \end{bmatrix}$, $\tilde{B}_i = \begin{bmatrix} B_iK_i \\ 0 \end{bmatrix}$, $\Gamma_i = \begin{bmatrix} -L_iC_i \\ L_iC_i \end{bmatrix}$, $\bar{B}_i = \begin{bmatrix} B_i \\ 0 \end{bmatrix}$, and $\tilde{g}_{ij}(\chi_i(t), \chi_j(t))= g_{ij}(\tilde{I}\chi_i(t), \tilde{I}\chi_j(t))$, $\tilde{I} = [I \quad I]$.

Remark 2.3. Notice $\chi_i(t) = [\hat{x}_i^T(t) \quad e_i^T(t)]^T$, thus the dynamic performance of the augmented system (12) reveals the dynamic of $\hat{x}_i(t)$ and $e_i(t)$. In addition, notice $x_i(t) = e_i(t) + \hat{x}_i(t)$, the dynamic performance of the augmented system (12) also reveals the dynamic of $x_i(t)$ in the closed-loop system (8). Furthermore, in light of (2), we have

$$\left\|\tilde{g}_{ij}\left(\chi_i(t), \chi_j(t)\right)\right\|^2 \le \left\|\tilde{M}_i\chi_i(t)\right\|^2 + \left\|\tilde{M}_{ij}\chi_j(t)\right\|^2, \quad (13)$$

where $\tilde{M}_i = [M_i \quad M_i]$, $\tilde{M}_{ij} = [M_{ij} \quad M_{ij}]$, $i \in N[1,n]$, $j \in \aleph_i$.

Lemma 2.1. ([40]) Considering a nonlinear fractional-order system

$$D^{\alpha}\xi(t) = f(\xi(t)),$$

which can be expressed using the following distributed model with internal variables $z(w,t)$

$$\begin{cases} \frac{\partial z(w,t)}{\partial t} = -wz(w,t) + f(\xi(t)) \\ \xi(t) = \int_0^{+\infty} \mu_{\alpha}(w)z(w,t)dw \end{cases},$$

where $\mu_{\alpha}(w) = \frac{\sin(n\pi)}{\pi}w^{-\alpha}$, $0 < \alpha < 1$.

Based on Lemma 2.1, the following distributed model with the internal variable $z_i(w,t)$ is associated with the augmented system (12).

$$\frac{\partial z_i(w,t)}{\partial t} = -wz_i(w,t) + \eta_i(t), \quad (14a)$$

$$\eta_i(t) = \tilde{A}_i\chi_i(t) + \sum_{j\in\aleph_i} \tilde{G}_{ij}\tilde{g}_{ij}\left(\chi_i(t), \chi_j(t)\right) + \tilde{B}_i\hat{e}_i(t)$$

$$+\beta_i(t)\Gamma_i h_i(\hat{x}_i(t)) + \gamma_i(t)\bar{B}_i f_i(\tilde{u}_i(t)), \tag{14b}$$

$$\chi_i(t) = \int_0^{+\infty} \mu_\alpha(w) z_i(w,t)dw \text{ with } \mu_\alpha(w) = \frac{\sin(n\pi)}{\pi} w^{-\alpha}, 0 < \alpha < 1. \tag{14c}$$

Definition 2.2. ([41,42]) The system (14) is said to be stochastically stable if there exists a scalar $\sigma > 0$ such that every solution $z(w,t;\varphi) = [z_1(w,t;\varphi_1), \quad z_2(w,t;\varphi_2), \cdots, \quad z_n(w,t;\varphi_n)]$ satisfies

$$\mathbf{E}\{\|z(w,t;\varphi)\|^2\} \le \sigma \mathbf{E}\{\|\varphi\|^2\}, \ \forall t \ge 0,$$

where φ_i is the initial point of i^{th} subsystem, and $\varphi = [\varphi_1, \varphi_2, \cdots, \varphi_n]$.

Lemma 2.2. ([43]) Given matrix $C \in \mathbf{R}^{m\times n}$ with $rank(C) = m$, the singular value decomposition is $C = U[C_0 \quad 0]V^T$, where $C_0 \in \mathbf{R}^{m\times m}$is a positive definite diagonal matrix, $U \in \mathbf{R}^{m\times m}$ and $V \in \mathbf{R}^{n\times n}$ are unitary matrices. Then for a matrix $P = P^T \in \mathbf{R}^{n\times n}$, there exists a matrix $Z \in \mathbf{R}^{m\times m}$ such that $CP = ZC$, if and only if

$$P = V\begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} V^T,$$

where $P_1 \in \mathbf{R}^{m\times m}$, $P_2 \in \mathbf{R}^{(n-m)\times(n-m)}$.

3. Main results

In this section, the stability and stabilization problem will be investigated for the system (12). A sufficient condition of the stochastic stability of the system (12) and the computing method of controller gains and observer gains will be presented respectively.

Theorem 3.1. Given scalars $0 < \alpha < 1$, $0 \le \bar{\beta}_i \le 1$, $0 \le \bar{\gamma}_i \le 1$, $F_i > 0$, $\delta_i > 0$, integer $n > 0$, matrices $0 < M_i \in \mathbf{R}^{n_i\times n_i}$, $M_{ij} \in \mathbf{R}^{n_i\times n_i}$ and $H_i \in \mathbf{R}^{n_i\times n_i}$ and the system parameters in IFOS (1). The IFOS (12) is stochastically stable if there exist matrices $0 < P_i = P_i^T \in \mathbf{R}^{2n_i\times 2n_i}$, the controller gains $K_i \in \mathbf{R}^{p_i\times n_i}$ and observer gains $L_i \in \mathbf{R}^{n_i\times m_i}$, such that for any $i \in N[1,n]$ and $j \in \aleph_i$, the following condition (15) holds.

$$\Psi_i = \begin{bmatrix} \Phi_i & P_i\tilde{B}_i & \bar{\beta}_i P_i \Gamma_i & \bar{\gamma}_i P_i \bar{B}_i & \Omega_i \\ * & -I & 0 & 0 & 0 \\ * & * & -I & 0 & 0 \\ * & * & * & -I & 0 \\ * & * & * & * & -I \end{bmatrix} < 0, \tag{15}$$

where $\Phi_i = \tilde{A}_i^T P_i + P_i \tilde{A}_i + \delta_i \bar{I}^T \bar{I} + \bar{I}^T H_i^T H_i \bar{I} + F_i^2 \bar{I}^T K_i^T K_i \bar{I} + (n-1)\tilde{M}_i^T \tilde{M}_i + \sum_{j\in\aleph_i} \tilde{M}_{ji}^T \tilde{M}_{ji}$, $\Omega_i = [P_i\tilde{G}_{i1} \cdots \quad P_i\tilde{G}_{i(i-1)} \quad P_i\tilde{G}_{i(i+1)} \cdots \quad P_i\tilde{G}_{in}]$, $\tilde{M}_i = [M_i \quad M_i]$, $\tilde{M}_{ij} = [M_{ij} \quad M_{ij}]$, $\bar{I} = [I \quad 0]$.

Proof. By the Lyapunov function

$$V(t) = \sum_{i=1}^n \int_0^{+\infty} \mu_\alpha(w) z_i^T(w,t) P_i z_i(w,t) dw, \tag{16}$$

we have

$$\mathbf{E}\{\mathcal{L}V(t)\} = \mathbf{E}\Big\{\sum_{i=1}^{n}\int_0^{+\infty}\mu_\alpha(w)z_i^T(w,t)P_i[-wz_i(w,t)+\xi_i(t)]dw$$
$$+\sum_{i=1}^{n}\int_0^{+\infty}\mu_\alpha(w)[-wz_i(w,t)+\xi_i(t)]^{\boldsymbol{T}}P_iz_i(w,t)dw\Big\}$$
$$= \mathbf{E}\Big\{\sum_{i=1}^{n}\int_0^{+\infty}-2w\mu_\alpha(w)z_i^T(w,t)P_iz_i(w,t)dw\Big\}$$
$$+\sum_{i=1}^{n}\mathbf{E}\{\chi_i^T(t)P_i\xi_i(t)+\xi_i^T(t)P_i\chi_i(t)\}$$
$$= \mathbf{E}\Big\{\sum_{i=1}^{n}\int_0^{+\infty}-2w\mu_\alpha(w)z_i^T(w,t)P_iz_i(w,t)dw\Big\}$$
$$+\sum_{i=1}^{n}\chi_i^T(t)P_i\big[\tilde{A}_i\chi_i(t)+\sum_{j\in\aleph_i}\tilde{G}_{ij}\tilde{g}_{ij}+\tilde{B}_i\hat{e}_i(t)+\bar{\beta}_i\Gamma_ih_i\big(\hat{x}_i(t)\big)+\bar{\gamma}_i\bar{B}_if_i\big(\tilde{u}_i(t)\big)\big]$$
$$+\sum_{i=1}^{n}\big[\tilde{A}_i\chi_i(t)+\sum_{j\in\aleph_i}\tilde{G}_{ij}\tilde{g}_{ij}+\tilde{B}_i\hat{e}_i(t)+\bar{\beta}_i\Gamma_ih_i\big(\hat{x}_i(t)\big)+\bar{\gamma}_i\bar{B}_if_i\big(\tilde{u}_i(t)\big)\big]^TP_i\chi_i(t). \tag{17}$$

To simplify, we denote $\tilde{g}_{ij}\triangleq\tilde{g}_{ij}\left(\chi_i(t),\chi_j(t)\right)$ in (16). Note (4)–(7), (9) and (13), and notice the fact that

$$\sum_{i=1}^{n}\sum_{j\in\aleph_i}\chi_j^T(t)\big(\widetilde{M}_{ij}^T\widetilde{M}_{ij}\big)\chi_j(t)=\sum_{i=1}^{n}\sum_{j\in\aleph_i}\chi_i^T(t)\big(\widetilde{M}_{ji}^T\widetilde{M}_{ji}\big)\chi_i(t). \tag{18}$$

Then,

$$\sum_{i=1}^{n}\chi_i^T(t)\left((n-1)\widetilde{M}_i^T\widetilde{M}_i\right)\chi_i(t)+\sum_{i=1}^{n}\sum_{j\in\aleph_i}\chi_i^T(t)\big(\widetilde{M}_{ji}^T\widetilde{M}_{ji}\big)\chi_i(t)-\sum_{i=1}^{n}\sum_{j\in\aleph_i}\tilde{g}_{ij}^T\tilde{g}_{ij}\geq 0. \tag{19}$$

Thanks to the first term $\sum_{i=1}^{n}\int_0^{+\infty}-2w\mu_\alpha(w)z_i^T(w,t)P_iz_i(w,t)dw$ in (17) is always negative, thus,

$$\mathbf{E}\{\mathcal{L}V(t)\}\leq\sum_{i=1}^{n}\big\{\chi_i^T(t)\big(\tilde{A}_i^TP_i+P_i\tilde{A}_i\big)\chi_i(t)+2\chi_i^T(t)P_i\big(\sum_{j\in\aleph_i}\tilde{G}_{ij}\tilde{g}_{ij}\big)+2\chi_i^T(t)P_i\tilde{B}_i\hat{e}_i(t)$$
$$+2\chi_i^T(t)\bar{\beta}_iP_i\Gamma_ih_i\big(\hat{x}_i(t)\big)+2\chi_i^T(t)\bar{\gamma}_iP_i\bar{\mathrm{B}}_if_i\big(\tilde{u}_i(t)\big)+\delta_i\chi_i^T(t)\bar{I}^T\bar{I}\chi_i(t)-\hat{e}_i^T(t)\hat{e}_i(t)$$
$$+\chi_i^T(t)\bar{I}^TH_i^TH_i\bar{I}\chi_i(t)-h_i^T\big(\hat{x}_i(t)\big)h_i\big(\hat{x}_i(t)\big)$$
$$+\chi_i^T(t)\bar{I}^TK_i^TF_i^TF_iK_i\bar{I}\chi_i(t)-f_i^T\big(\tilde{u}_i(t)\big)f_i\big(\tilde{u}_i(t)\big)$$
$$+\chi_i^T(t)\left((n-1)\widetilde{M}_i^T\widetilde{M}_i\right)\chi_i(t)+\sum_{j\in\aleph_i}\chi_i^T(t)\big(\widetilde{M}_{ji}^T\widetilde{M}_{ji}\big)\chi_i(t)-\sum_{j\in\aleph_i}\tilde{g}_{ij}^T\tilde{g}_{ij}\big\}$$
$$=\sum_{i=1}^{n}\vartheta^T(t)\Psi_i\vartheta(t), \tag{20}$$

where,

$$\vartheta^T(t)=\big[\chi_i^T(t)\quad \hat{e}_i^T(t)\quad h_i^T\big(\hat{x}_i(t)\big)\quad f_i^T\big(\tilde{u}_i(t)\big)\quad [\tilde{g}_{i1}^T\cdots\quad\tilde{g}_{i(i-1)}^T\quad\tilde{g}_{i(i+1)}^T\cdots\tilde{g}_{in}^T]\big].$$

Hence, (15) implies $\mathbf{E}\{\mathcal{L}V(t)\} < 0$. Then, similar to [44], and according to Definition 2.2, it is said that the system (14) is stochastically asymptotically stable. It is equivalent to that the system (12) is stochastically asymptotically stable.

Theorem 3.2 Given scalars $0 < \alpha < 1$, $0 \le \bar{\beta}_i \le 1$, $0 \le \bar{\gamma}_i \le 1$, $F_i > 0$, $\delta_i > 0$, integer $n > 0$, matrices $0 < M_i \in \mathbf{R}^{n_i \times n_i}$, $M_{ij} \in \mathbf{R}^{n_i \times n_i}$ and $H_i \in \mathbf{R}^{n_i \times n_i}$ and the system parameters in IFOS (1). The IFOS (12) is stochastically stable if there exist matrices $0 < P_{i1} = P_{i1}^T \in \mathbf{R}^{n_i \times n_i}$, $0 < P_{i2} = P_{i2}^T \in \mathbf{R}^{n_i \times n_i}$, $X_i \in \mathbf{R}^{p_i \times m_i}$, $Y_i \in \mathbf{R}^{n_i \times m_i}$, such that for any $i \in N[1, n]$, the following condition (22) hold.

$$\begin{bmatrix} \tilde{\Phi}_i & Y_iC_i & B_iX_i & -\bar{\beta}_iY_iC_i & \bar{\gamma}_iB_i & 0 & \Pi_{i1} \\ * & \tilde{\Theta}_i & 0 & \bar{\beta}_iY_iC_i & 0 & \tilde{\Omega}_i & \Pi_{i2} \\ * & * & -2P_{i1}+I & 0 & 0 & 0 & 0 \\ * & * & * & -2P_{i2}+I & 0 & 0 & 0 \\ * & * & * & * & -I & 0 & 0 \\ * & * & * & * & * & -I & 0 \\ * & * & * & * & * & * & -I \end{bmatrix} < 0, \tag{21}$$

where,

$$\tilde{\Phi}_i = A_iP_{i1} - B_iX_i + P_{i1}A_i^T - X_i^TB_i^T,\ \tilde{\Theta}_i = A_iP_{i2} - Y_iC_i + P_{i2}A_i^T - C_i^TY_i^T,\ \tilde{n} = \sqrt{n-1},$$

$$\tilde{\Omega}_i = [G_{i1} \cdots \quad G_{i(i-1)} \quad G_{i(i+1)} \cdots \quad G_{in}],\ \begin{bmatrix} \Pi_{i1} \\ \Pi_{i2} \end{bmatrix} = \begin{bmatrix} \sqrt{\delta_i}P_{i1} & \tilde{n}P_{i1}M_i^T & P_{i1}\Xi_i & P_{i1}H_i^T & F_iX_i^T \\ 0 & \tilde{n}P_{i2}M_i^T & P_{i2}\Xi_i & 0 & 0 \end{bmatrix},$$

$$\Xi_i = \left[M_{1i}^T \cdots \quad M_{(i-1)i}^T \quad M_{(i+1)i}^T \cdots \quad M_{ni}^T\right],\ P_{i2} = V_i\begin{bmatrix} P_{i2}^a & 0 \\ 0 & P_{i2}^b \end{bmatrix}V_i^T,\ C_i = U_i[C_{oi} \quad 0]V_i^T,$$

U_i and V_i are unitary matrices. In this case, the decentralized event-triggered controller gains can be computed with $K_i = X_iP_{i1}^{-1}$ and decentralized observer gains can be given by $L_i = Y_iU_iC_{oi}(P_{i2}^a)^{-1}{C_{oi}}^{-1}U_i^T$.

Proof. Note the fact that $-2P_{i1} + I \ge -P_{i1}^2$ and $-2P_{i2} + I \ge -P_{i2}^2$, one can obtain that (21) holds implies the following inequality (22) holds.

$$\begin{bmatrix} \tilde{\Phi}_i & Y_iC_i & B_iX_i & -\bar{\beta}_iY_iC_i & \bar{\gamma}_iB_i & 0 & \Pi_{i1} \\ * & \tilde{\Theta}_i & 0 & \bar{\beta}_iY_iC_i & 0 & \tilde{\Omega}_i & \Pi_{i2} \\ * & * & -P_{i1}^2 & 0 & 0 & 0 & 0 \\ * & * & * & -P_{i2}^2 & 0 & 0 & 0 \\ * & * & * & * & -I & 0 & 0 \\ * & * & * & * & * & -I & 0 \\ * & * & * & * & * & * & -I \end{bmatrix} < 0. \tag{22}$$

Take the congruent transformation for the matrix in (22) by $diag\{P_{i1}^{-1}, P_{i2}^{-1}, P_{i1}^{-1}, P_{i2}^{-1}, I, I, I\}$, then denote $P_{i1}^{-1} \triangleq \bar{P}_{i1}$ and $P_{i2}^{-1} \triangleq \bar{P}_{i2}$, and notice the computed controller gains and observer gains, according to Lemma 2.2, one can obtain that (22) equivalent to (23).

$$\begin{bmatrix} \bar{\Phi}_i & \bar{P}_{i1}L_iC_i & \bar{P}_{i1}B_iK_i & -\bar{\beta}_i\bar{P}_{i1}L_iC_i & \bar{\gamma}_i\bar{P}_{i1}B_i & 0 & \bar{\Pi}_{i1} \\ * & \bar{\Theta}_i & 0 & \bar{\beta}_i\bar{P}_{i2}L_iC_i & 0 & \bar{P}_{i2}\tilde{\Omega}_i & \bar{\Pi}_{i2} \\ * & * & -I & 0 & 0 & 0 & 0 \\ * & * & * & -I & 0 & 0 & 0 \\ * & * & * & * & -I & 0 & 0 \\ * & * & * & * & * & -I & 0 \\ * & * & * & * & * & * & -I \end{bmatrix} < 0, \tag{23}$$

where $\bar{\Phi}_i = \bar{P}_{i1}A_i - \bar{P}_{i1}B_iK_i + A_i^T\bar{P}_{i1} - K_i^TB_i^T\bar{P}_{i1}$, $\bar{\Theta}_i = \bar{P}_{i2}A_i - \bar{P}_{i2}L_iC_i + A_i^T\bar{P}_{i2} - C_i^TL_i^T\bar{P}_{i2}$, $\begin{bmatrix} \bar{\Pi}_{i1} \\ \bar{\Pi}_{i2} \end{bmatrix} = \begin{bmatrix} \sqrt{\delta_i}I & M_i^T & \Xi_i & H_i^T & F_iX_i^T \\ 0 & \tilde{n}M_i^T & \Xi_i & 0 & 0 \end{bmatrix}$.

Then, denote $P_i = \begin{bmatrix} \bar{P}_{i1} & 0 \\ 0 & \bar{P}_{i2} \end{bmatrix}$, by Schur Complement, one can obtain that (23) meets (15) in Theorem 3.1. It is to say that the IFOS (12) is stochastically stable under the decentralized observer-based event-triggered controller (6).

4. Numerical example

Consider an IFOS that consists of two subsystems in the form of (1) with specific parameters described in the following.
Subsystem 1:

$$D^{0.5}x_1(t) = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & -0.6 & 2.4 & 1.7 \\ 0 & 0 & -2.8 & 2.8 \\ 0 & -0.6 & 0 & -1 \end{bmatrix} x_1(t) + \begin{bmatrix} 0.1 \\ -0.2 \\ 0.2 \\ 0.3 \end{bmatrix} g_{12}(t) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} u_1(t),$$

$$y_1(t) = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} x_1(t).$$

Subsystem 2:

$$D^{0.5}x_2(t) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -0.6 & 1.4 & 0.7 \\ 0 & 0 & -2.8 & 1.8 \\ 0 & -0.6 & 0 & -1 \end{bmatrix} x_2(t) + \begin{bmatrix} 0.1 \\ -0.2 \\ 0.2 \\ 0.2 \end{bmatrix} g_{21}(t) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} u_2(t),$$

$$y_2(t) = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} x_2(t).$$

Given parameters $\bar{\beta}_i = 0.3$, $\bar{\gamma}_i = 0.3$, $(i = 1,2)$, $\delta_1 = 0.1024$, $\delta_2 = 0.16$, T=0.05s and the interconnections $g_{ij}\left(x_i(t), x_j(t)\right) = \sin\left(M_ix_i(t) - M_{ij}x_j(t)\right)$, where $M_i = \begin{bmatrix} 0.1 & 0 & 0 & 0 \end{bmatrix}$, $M_{ij} = \begin{bmatrix} 0.1 & 0 & 0 & 0 \end{bmatrix}$, $i = 1,2; j \neq i$. The stochastic attacks on the observer output of i^{th} subsystem are described as

$$h_i\left(\hat{x}_i(t)\right) = -\left[\tanh\left(0.02\hat{x}_{i4}(t)\right) \quad \tanh\left(0.02\hat{x}_{i3}(t)\right) \quad \tanh\left(0.02\hat{x}_{i2}(t)\right) \quad \tanh\left(0.02\hat{x}_{i1}(t)\right)\right]^T,$$

in which $\hat{x}_i(t) = [\hat{x}_{i1}^T(t) \quad \hat{x}_{i2}^T(t) \quad \hat{x}_{i3}^T(t) \quad \hat{x}_{i4}^T(t)]^T$. $h_i(\hat{x}_i(t))$ satisfies Assumption 1 with $H_1 = H_2 = 0.02I$, $(i = 1,2)$. The stochastic attacks on the control input of i^{th} subsystem are described as $f_i(\tilde{u}_i(t)) = 0.2\tilde{u}_i(t)\sin(2t)$, which satisfies Assumption 2 with $F_1 = F_2 = 0.2$.

Solve the LMIs (21) in Theorem 3.2, the decentralized event-triggered controller gains and observer gains can be obtained.

$$\begin{aligned} K_1 &= [0.9197 \quad 0.6036 \quad 0.4909 \quad 1.0815], \\ K_2 &= [1.4218 \quad 1.1979 \quad 0.5827 \quad 1.0617], \\ L_1 &= [1.6799 \quad -0.5288 \quad 2.2421 \quad -0.4294]^T, \\ L_2 &= [0.8942 \quad -0.3794 \quad 0.6540 \quad -0.0164]^T. \end{aligned}$$

For simulation purposes, the sampling period is set as 0.05, and the initial points $x_1(0) = [0.1 \quad -0.2 \quad 0.1 \quad -1]^T$ and $x_2(0) = [-0.2 \quad 0.3 \quad 0.2 \quad 1]^T$ are taken for subsystem 1 and subsystem 2, respectively. The instants of two classes of cyber-attacks are depicted by the Bernoulli distribution in Figures 1 and 2. Figure 3 depicts the ETC release instants of the two subsystems. Figure 4 describes the actual inputs $u_i(t)$ under attacks for two subsystems. The state trajectories and observer error trajectories of the closed-loop subsystems are depicted in Figures 5 and 6. The simulation results show that the closed-loop system is stochastic stable under the decentralized observer-based event-triggered control.

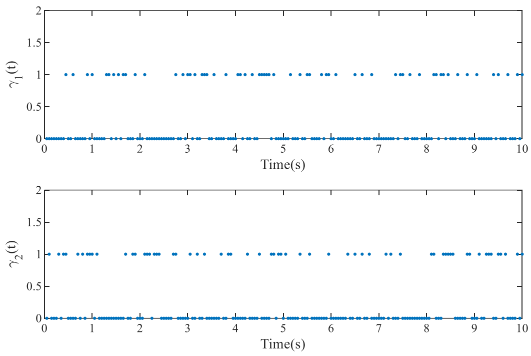

Figure 1. Attack instant to observers.

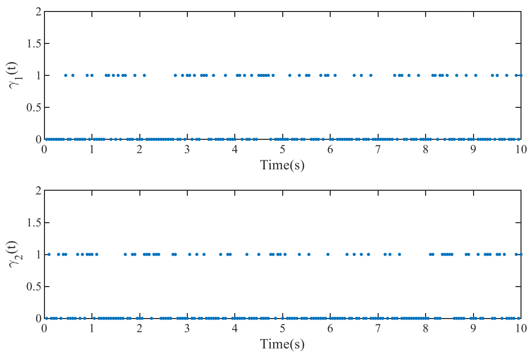

Figure 2. Attack instant to control inputs.

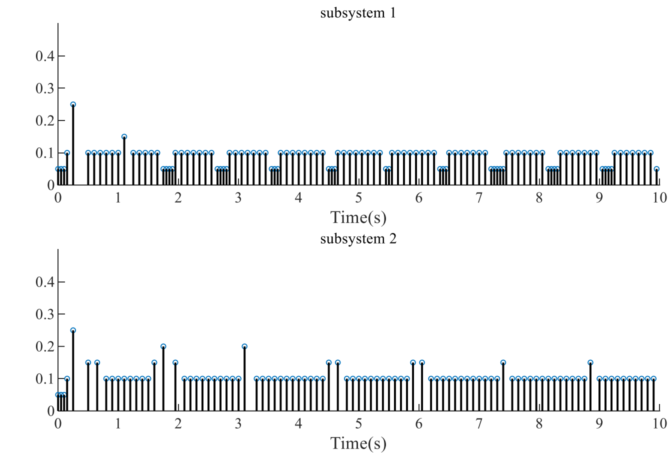

Figure 3. Event-triggered release instants.

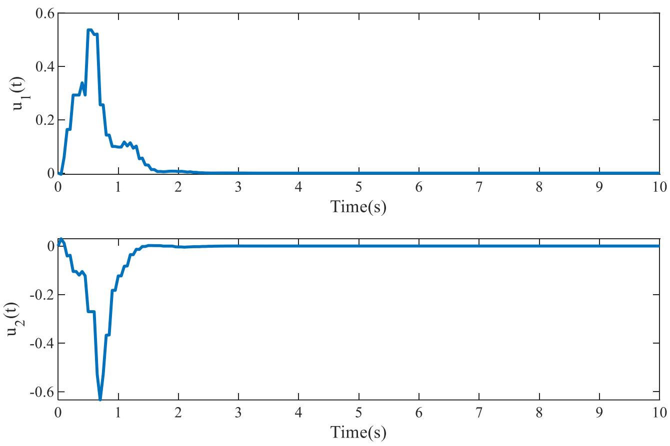

Figure 4. Actual control inputs under attacks.

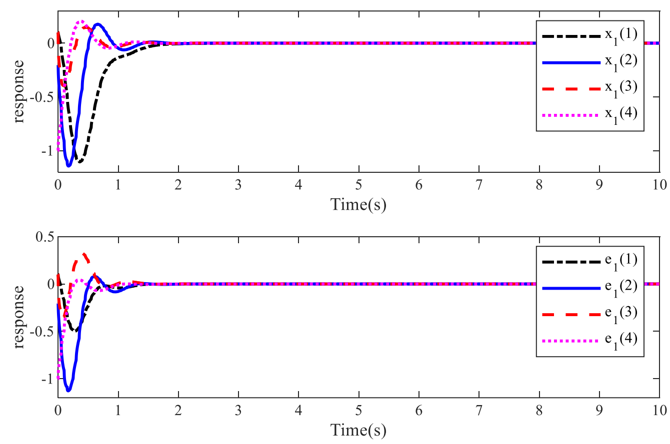

Figure 5. State and error trajectories of the closed-loop subsystem 1.

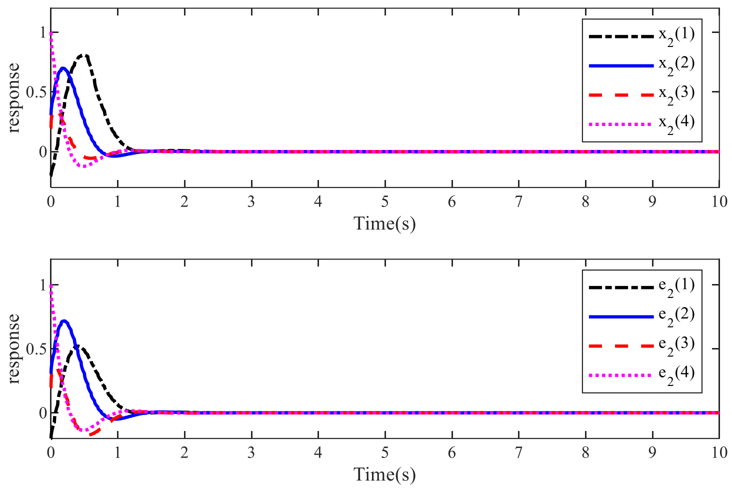

Figure 6. State and error trajectories of the closed-loop subsystem 2.

5. Conclusions

We have investigated the decentralized control problem for an IFOS subject to stochastic cyber-attacks. The co-designed approach has been utilized for the decentralized observer and the decentralized event-triggered controller. By diffusive representation and the Lyapunov method, sufficient conditions for the augmented IFOS stability have been obtained. The constructed augmentation systems consist of observer systems and error systems. Thus, the performance of observer systems, error systems and original systems is consistent with the performance of the augmented systems. Furthermore, the stabilization problem of IFOS has been described in the form of LMIs. The simulation results have illustrated the effectiveness of the proposed method

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest.

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