Research Article

Centralized Data-Sampling Approach for Global $O(t^{-\alpha})$ Synchronization of Fractional-Order Neural Networks with Time Delays

Jin-E Zhang

Hubei Normal University, Hubei 435002, China

Correspondence should be addressed to Jin-E Zhang; zhang86021205@163.com

Received 8 November 2016; Revised 18 December 2016; Accepted 9 January 2017; Published 9 February 2017

Academic Editor: Qasem M. Al-Mdallal

Copyright © 2017 Jin-E Zhang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In this paper, the global $O(t^{-\alpha})$ synchronization problem is investigated for a class of fractional-order neural networks with time delays. Taking into account both better control performance and energy saving, we make the first attempt to introduce centralized data-sampling approach to characterize the $O(t^{-\alpha})$ synchronization design strategy. A sufficient criterion is given under which the drive-response-based coupled neural networks can achieve global $O(t^{-\alpha})$ synchronization. It is worth noting that, by using centralized data-sampling principle, fractional-order Lyapunov-like technique, and fractional-order Leibniz rule, the designed controller performs very well. Two numerical examples are presented to illustrate the efficiency of the proposed centralized data-sampling scheme.

1. Introduction

Fractional-order calculus has gained an increasing attention in physical systems and engineering systems. Fractional-order dynamic systems containing fractional derivatives and integrals have been investigated in the field of control systems [1–19]. Investigating analytical skills in fractional-order dynamic systems is one important theme. However, it is considered that many control schemes for fractional differential equation are only a mathematical concept. A lot of control methods in integer-order dynamic systems cannot be introduced to fractional-order dynamic systems [2, 3].

As a kind of the important dynamic systems, the concept of neurodynamic systems can be traced back to the early 1940s. Neurodynamic systems behave like a synthesizer evaluating the performance of system itself via the topology structure. In recent years, modeling fractional phenomenon to neurodynamic systems has been developed in an effort to improve the neurodynamic processes [2, 3, 14, 16]. Appealing feature of fractional-order neurodynamic systems is that the infinite memory property can take the past inherited information into account, which well suits describing complex dynamic processes. For control system

applications, fractional-order neurodynamic systems have greatly expanded systems of conventional difference equations, which provide an adaptive control system for standard application.

Data-sampling control of systems has been studied in a number of publications. Actually, as stated in [20–30], for complex or multivariable control systems, it is unrealistic or even impossible to sample all real-time physical signals at one single rate. In such situation, one is forced to use multirate data-sampling control. Multirate data-sampling control conditions have been derived there which are less conservative [31–35]. Multirate data-sampling control can achieve what single-rate data-sampling control cannot, for instance, gain margin improvement, centralized control, and decentralized control.

Many control schemes have been established for complex control systems, such as adaptive control [36, 37] and sliding mode control [38]. In view of the feature of fractional-order systems, compared with other control strategies, centralized data-sampling scheme is more applicable for implementation in fractional-order systems. For one thing, centralized data-sampling scheme itself is relatively cheaper and simpler to operate. Unlike a lot of data-sampling designs, these

schemes are usually designed for continuous sampling, and the control cost is very high. For another thing, considering that the system structures of fractional-order systems are complex and ever changing, which may have unpredictable nonlinear effects, it is more reasonable and implementable for centralized data-sampling only carried out at part of timing nodes.

In this paper, a centralized data-sampling architecture enabled by low-bandwidth communication is proposed. The centralized data-sampling approach is developed to globally $O(t^{-\alpha})$ synchronize the drive-response-based coupled fractional-order neural networks with time delays. And then we present an intelligent control method for designing synchronization scheme based on centralized data-sampling principle, fractional-order Lyapunov-like technique, and fractional-order Leibniz rule. The obtained results provide novel and higher performance extension for the designed controller. The use of centralized data-sampling approach facilitates utilizing low-bandwidth communication to transmit harmonic signals. The operation principle and numerical examples based on computer simulations are also presented.

2. Preliminaries and Problem Formulation

2.1. Notation. For n -dimensional vector $v = (v_1, v_2, \dots, v_n)^T$, the norm of vector v is recorded as $\|v\| = \sum_{i=1}^n |v_i|$. Denote $\mathcal{C}^l([t_0, +\infty), \mathcal{R}^n)$ as the space of l -order continuous and differentiable functions from $[t_0, +\infty)$ into $\mathcal{R}^n$. $\mathcal{C}_\tau := \mathcal{C}([-\tau, 0], \mathcal{R})$ is a Banach space of all continuous functions $\varphi : [-\tau, 0] \rightarrow \mathcal{R}$. For any $\varphi \in \mathcal{C}_\tau$, let $\|\varphi\|_{\mathcal{C}} = \sup_{s \in [-\tau, 0]} \|\varphi(s)\|$.

2.2. Preliminaries. In order to facilitate understanding, we first introduce some concepts of fractional calculation.

Fractional integral with order $\alpha > 0$ of function $\mathcal{F}(t)$ is characterized as

$${}^{\text{RL}}D_t^{-\alpha} \mathcal{F}(t) = \frac{1}{\Gamma(\alpha)} \int_{t_0}^t (t-s)^{\alpha-1} \mathcal{F}(s) ds, \quad (1)$$

where $t \geq t_0$, $\Gamma(\cdot)$ is the Gamma function, which is defined as

$$\Gamma(\alpha) = \int_{t_0}^{+\infty} s^{\alpha-1} \exp\{-s\} ds. \quad (2)$$

Riemann-Liouville derivative with order $\alpha > 0$ of function $\mathcal{F}(t)$ is characterized as

$${}^{\text{RL}}D_t^\alpha \mathcal{F}(t) = \frac{1}{\Gamma(n-\alpha)} \frac{d^n}{dt^n} \int_{t_0}^t \frac{\mathcal{F}(s)}{(t-s)^{\alpha-n+1}} ds, \quad (3)$$

where $t \geq t_0$, $n-1 < \alpha < n$, and n is a positive integer.

Caputo derivative with order $\alpha > 0$ of function $\mathcal{F}(t) \in \mathcal{C}^{n+1}([t_0, +\infty), \mathcal{R})$ is characterized as

$${}_t^C D_t^\alpha \mathcal{F}(t) = \frac{1}{\Gamma(n-\alpha)} \int_{t_0}^t \frac{\mathcal{F}^{(n)}(s)}{(t-s)^{\alpha-n+1}} ds, \quad (4)$$

where $t \geq t_0$, $n-1 < \alpha < n$, and n is a positive integer.

In this paper, consider a class of fractional-order neural networks with time delays governed by

$$\begin{aligned} {}_t^C D_t^\alpha x(t) &= -Dx(t) + Ag(x(t)) + Bf(x(t-\tau(t))) \\ &\quad + I, \\ y(t) &= Cx(t), \end{aligned} \quad (5)$$

where $0 < \alpha < 1$, $x(t) = (x_1(t), x_2(t), \dots, x_n(t))^T \in \mathcal{R}^n$ is the state vector, $D = \text{diag}(d_1, d_2, \dots, d_n)$ is a positive diagonal matrix, $A = (a_{ij})_{n \times n} \in \mathcal{R}^{n \times n}$ and $B = (b_{ij})_{n \times n} \in \mathcal{R}^{n \times n}$ denote the weight matrix and the delayed weight matrix, respectively, $\tau(t)$ represents the transmission delay satisfying $0 \leq \tau(t) \leq \tau$, $g(x(t)) = (g_1(x_1(t)), g_2(x_2(t)), \dots, g_n(x_n(t)))^T \in \mathcal{R}^n$ and $f(x(t-\tau(t))) = (f_1(x_1(t-\tau(t))), f_2(x_2(t-\tau(t))), \dots, f_n(x_n(t-\tau(t))))^T \in \mathcal{R}^n$ denote the activation functions at times t and $t-\tau(t)$, respectively, $I = (I_1, I_2, \dots, I_n)^T \in \mathcal{R}^n$ is the bias, $C = (c_{ij})_{m \times n} \in \mathcal{R}^{m \times n}$ is a constant matrix, and $y(t) = (y_1(t), y_2(t), \dots, y_m(t))^T \in \mathcal{R}^m$ is the output vector.

Obviously, system (5) is a more general model. In [2, 16], the model is a fractional-order system without time-delay. By comparing the system models, system (5) contains some existing fractional-order neural networks.

The initial condition of system (5) is $x(t) = \chi(t) \in \mathcal{C}_\tau$.

In addition, in (5), the activation functions $g(\cdot)$ and $f(\cdot)$ are global Lipschitz; that is, for $i = 1, 2, \dots, n$, there exist positive constants $G_i > 0$ and $F_i > 0$ such that

$$\begin{aligned} |g_i(u) - g_i(v)| &\leq G_i |u - v|, \quad \text{for any } u \in \mathcal{R}, v \in \mathcal{R}, \\ |f_i(u) - f_i(v)| &\leq F_i |u - v|, \quad \text{for any } u \in \mathcal{R}, v \in \mathcal{R}. \end{aligned} \quad (6)$$

2.3. Problem Formulation. In this paper, consider system (5) as the master/drive system, and then the slave/response system is described as

$$\begin{aligned} {}_t^C D_t^\alpha \hat{x}(t) &= -D\hat{x}(t) + Ag(\hat{x}(t)) + Bf(\hat{x}(t-\tau(t))) \\ &\quad + I + u(t), \\ \hat{y}(t) &= C\hat{x}(t), \end{aligned} \quad (7)$$

where $u(t) = (u_1(t), u_2(t), \dots, u_n(t))^T \in \mathcal{R}^n$ is the controller to be designed.

The initial condition of system (7) is $\hat{x}(t) = \hat{\chi}(t) \in \mathcal{C}_\tau$.

Define $e(t) = \hat{x}(t) - x(t) \in \mathcal{R}^n$, from (5) and (7); then we can obtain the error dynamics system

$$\begin{aligned} {}_t^C D_t^\alpha e(t) &= -De(t) + Ag(e(t)) + Bf(e(t-\tau(t))) \\ &\quad + u(t), \end{aligned} \quad (8)$$

where

$$\begin{aligned} g(e(t)) &= (g_1(e_1(t)), g_2(e_2(t)), \dots, g_n(e_n(t)))^T \\ &= g(\hat{x}(t)) - g(x(t)), \end{aligned}$$

$$f(e(t-\tau(t))) = (f_1(e_1(t-\tau(t))), f_2(e_2(t-\tau(t))), \dots, f_n(e_n(t-\tau(t))))^T$$

$$\begin{aligned} & \dots, f_n(e_n(t - \tau(t)))^T = f(\hat{x}(t - \tau(t))) \\ & - f(x(t - \tau(t))). \end{aligned} \quad (9)$$

The initial condition of system (8) is $e(t) = \psi(t) := \hat{\chi}(t) - \chi(t) \in \mathcal{C}_\tau$.

In our control design, the structure-dependent centralized data-sampling is used. Moreover, the measured output of error dynamics system is sampled and then the data-sampling information is sent to the controller of the response system as

$$\begin{aligned} z(t) &= \hat{y}(t_k) - y(t_k) = Ce(t_k), \\ t &\in [t_k, t_{k+1}), \quad k = 0, 1, 2, \dots, \end{aligned} \quad (10)$$

where $z(t) \in \mathbb{R}^m$ represents the output of (8) and t_k denotes the sampling instant satisfying $\lim_{k \rightarrow +\infty} t_k = +\infty$.

To study global $O(t^{-\alpha})$ synchronization, next, we will introduce some related definitions.

Definition 1. For dynamic system

$${}^C_{t_0} D_t^\alpha \mathcal{X}(t) = \mathcal{F}(t, \mathcal{X}_t), \quad (11)$$

where $\mathcal{X}_t(\theta) = \mathcal{X}(t + \theta)$ is defined on $-\tau \leq \theta \leq 0$, the initial condition of system (11) is $\mathcal{X}(t) = \varphi(t) \in \mathcal{C}_\tau$. System (11) is said to be globally $O(t^{-\alpha})$ stable if there exists a positive constant $M > 0$ such that $\|\mathcal{X}(t, t_0, \varphi)\| \leq M\|\varphi\|_\mathcal{C} O(t^{-\alpha})$ for any $\varphi \in \mathcal{C}_\tau$ and $t \geq t_0$.

Remark 2. Convergence of fractional-order systems is totally different from conventional exponential convergence or absolute convergence, which possesses abnormal convergence behavior. In addition, according to Definition 1, global $O(t^{-\alpha})$ stability and global Mittag-Leffler stability are “essentially the same.” On Mittag-Leffler stability, please see some publications [2, 16].

Definition 3. For the master/drive system

$${}^C_{t_0} D_t^\alpha \mathcal{X}(t) = \mathcal{F}(t, \mathcal{X}_t) \quad (12)$$

and the slave/response system

$${}^C_{t_0} D_t^\alpha \mathcal{Y}(t) = \mathcal{F}(t, \mathcal{Y}_t, u(t)), \quad (13)$$

where $\mathcal{X}_t(\theta) = \mathcal{X}(t + \theta)$ and $\mathcal{Y}_t(\theta) = \mathcal{Y}(t + \theta)$ are defined on $-\tau \leq \theta \leq 0$, the initial conditions for systems (12) and (13) are $\mathcal{X}(t) = \phi(t) \in \mathcal{C}_\tau$ and $\mathcal{Y}(t) = \hat{\phi}(t) \in \mathcal{C}_\tau$, respectively. The coupled systems (12) and (13) are said to be globally $O(t^{-\alpha})$ synchronized if the zero solution of the error dynamics system

$${}^C_{t_0} D_t^\alpha \mathcal{E}(t) = \mathcal{F}(t, \mathcal{Y}_t, u(t)) - \mathcal{F}(t, \mathcal{X}_t) \quad (14)$$

is globally $O(t^{-\alpha})$ stable, where $\mathcal{E}(t) = \mathcal{Y}(t) - \mathcal{X}(t)$.

3. Main Results

Based on the discussion in preceding section, then the data-sampling controller can be designed as

$$\begin{aligned} u(t) &= Kz(t) = KCe(t_k), \\ t &\in [t_k, t_{k+1}), \quad k = 0, 1, 2, \dots, \end{aligned} \quad (15)$$

where $K = (\mathfrak{K}_{ij})_{m \times m} \in \mathbb{R}^{m \times m}$ is the constant gain matrix to be determined. Therefore, the error dynamics system can be transformed into the following form:

$$\begin{aligned} {}^C_{t_0} D_t^\alpha e(t) &= -De(t) + Ag(e(t)) + Bf(e(t - \tau(t))) \\ &+ KCe(t_k), \quad t \in [t_k, t_{k+1}). \end{aligned} \quad (16)$$

For technical convenience, we also give mathematical expression for (16) represented by components: for $i = 1, 2, \dots, n$,

$$\begin{aligned} {}^C_{t_0} D_t^\alpha e_i(t) &= -d_i e_i(t) + \sum_{j=1}^n a_{ij} g_j(e_j(t)) \\ &+ \sum_{j=1}^n b_{ij} f_j(e_j(t - \tau(t))) \\ &+ \sum_{\ell=1}^m \sum_{h=1}^m \mathfrak{K}_{\ell h} \mathfrak{G}_{hi} e_i(t_k), \quad t \in [t_k, t_{k+1}). \end{aligned} \quad (17)$$

Before we began to develop theoretical criterion, we first state an important lemma, which will be used in the proving process.

Lemma 4 (see [3]). If $\mathcal{F} \in \mathcal{C}^1([0, +\infty), \mathbb{R})$, then the following properties hold:

- (1) ${}^C_{t_0} D_t^\alpha \mathcal{F}(t) = {}^{\text{RL}}_{t_0} D_t^\alpha \mathcal{F}(t) - (\mathcal{F}(t_0)/\Gamma(1 - \alpha))(t - t_0)^{-\alpha}$.
- (2) If $\mathcal{F}(t)$ and $\mathcal{G}(t)$ and their all derivatives are continuous in $[t_0, t]$, then

$$\begin{aligned} {}^{\text{RL}}_{t_0} D_t^\alpha (\mathcal{G}(t) \mathcal{F}(t)) &= \sum_{\kappa=0}^n \frac{d^\kappa \mathcal{G}(t)}{dt^\kappa} \binom{\alpha}{\kappa} {}^{\text{RL}}_{t_0} D_t^{\alpha-\kappa} \mathcal{F}(t) \\ &- R_n^\alpha(t), \end{aligned} \quad (18)$$

where $0 < \alpha < 1$, $n \geq \alpha$,

$$\begin{aligned} R_n^\alpha(t) &= \frac{(-1)^n (t - \alpha)^{n-\alpha+1}}{n! \Gamma(-\alpha)} \int_0^1 \int_0^1 \mathcal{F}_\alpha(t, \xi, \eta) d\xi d\eta, \\ \mathcal{F}_\alpha(t, \xi, \eta) &= \mathcal{F}(t_0 + \eta(t - t_0)) \mathcal{G}^{n+1}(t_0 + (t - t_0)(\xi + \eta - \xi\eta)), \\ \binom{\alpha}{\kappa} &= \frac{\Gamma(\alpha + 1)}{\kappa! \Gamma(\alpha - \kappa + 1)}. \end{aligned} \quad (19)$$

Theorem 5. If there exist positive constants $r > \tau \geq 0$ and $\beta_i > 0$ ($i = 1, 2, \dots, n$) such that

$$d_i - \frac{1}{\beta_i} \sum_{j=1}^n \beta_j |a_{ij}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{K}_{\ell h}| |\mathfrak{G}_{hi}| - \left(\frac{r}{r-\tau} \right)^\alpha \sum_{j=1}^n \frac{\beta_j}{\beta_i} |b_{ij}| F_j - \frac{1+\alpha}{r^\alpha \Gamma(2-\alpha)} \geq 0, \quad (20)$$

for $i = 1, 2, \dots, n$, set t_{k+1} as the sampling time point such that

$$t_{k+1} = \sup_{\delta \geq t_k} \left\{ \delta : |e_i(t_k)| \leq \beta_i \max_{1 \leq \sigma \leq n} \left[\frac{|e_\sigma(t)|}{\beta_\sigma} \right], \forall t \in [t_k, \delta), i = 1, 2, \dots, n \right\} \quad (21)$$

for all $k = 0, 1, 2, \dots$; then system (17) is globally $O(t^{-\alpha})$ stable. That is, the drive-response-based coupled systems (5) and (7) can reach global $O(t^{-\alpha})$ synchronization.

Proof. Consider the Lyapunov functions candidate as

$$\begin{aligned} \mathcal{W}(t) &= \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\}, \\ \mathcal{V}(t) &= (t - t_0 + r)^\alpha \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \end{aligned} \quad (22)$$

and set

$$\begin{aligned} \overline{\mathcal{W}}(t) &= \sup_{-\tau \leq \theta \leq t} \mathcal{W}(\theta), \\ \overline{\mathcal{V}}(t) &= \sup_{-\tau \leq \theta \leq t} \mathcal{V}(\theta), \end{aligned} \quad (23)$$

for $t \geq t_0$. $\square$

Using Lemma 4, we can obtain

$$\begin{aligned} {}^C D_t^\alpha \mathcal{V}(t) &= {}^{\text{RL}} D_t^\alpha \mathcal{V}(t) - \frac{\mathcal{V}(t_0)}{\Gamma(1-\alpha)} (t - t_0)^{-\alpha} \\ &= {}^{\text{RL}} D_t^\alpha \left((t - t_0 + r)^\alpha \cdot \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \right) \\ &\quad - \frac{r^\alpha \max \{|e_i(t_0)|/\beta_i, i = 1, 2, \dots, n\}}{\Gamma(1-\alpha)} (t - t_0)^{-\alpha} \\ &\leq (t - t_0 + r)^\alpha {}^C D_t^\alpha \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\ &\quad + (t - t_0 + r)^\alpha \frac{\max \{|e_i(t_0)|/\beta_i, i = 1, 2, \dots, n\}}{\Gamma(1-\alpha)} (t - t_0)^{-\alpha} + \alpha^2 (t - t_0 + r)^{\alpha-1} {}^{\text{RL}} D_t^{\alpha-1} \end{aligned}$$

$$\cdot \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} + \frac{\alpha^2 (\alpha - 1)^2}{2} (t - t_0 + r)^{\alpha-2} \times {}^{\text{RL}} D_t^{\alpha-2}$$

$$\begin{aligned} &\cdot \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\ &\quad - \frac{r^\alpha \max \{|e_i(t_0)|/\beta_i, i = 1, 2, \dots, n\}}{\Gamma(1-\alpha)} (t - t_0)^{-\alpha} \\ &\leq (t - t_0 + r)^\alpha {}^C D_t^\alpha \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\ &\quad + \left[\left(\frac{t - t_0 + r}{t - t_0} \right)^\alpha - \left(\frac{r}{t - t_0} \right)^\alpha \right] \\ &\quad \cdot \frac{\max \{|e_i(t_0)|/\beta_i, i = 1, 2, \dots, n\}}{\Gamma(1-\alpha)} + \alpha^2 (t - t_0 + r)^{\alpha-1} {}^{\text{RL}} D_t^{\alpha-1} \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\ &\quad + \frac{\alpha^2 (\alpha - 1)^2}{2} (t - t_0 + r)^{\alpha-2} \times {}^{\text{RL}} D_t^{\alpha-2} \\ &\quad \cdot \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \leq (t - t_0 + r)^\alpha \\ &\quad \cdot {}^C D_t^\alpha \mathcal{W}(t) + (1 + 2\alpha) \frac{\overline{\mathcal{V}}(t)}{r^\alpha \Gamma(1-\alpha)} + \alpha^2 (t - t_0 + r)^{\alpha-1} {}^{\text{RL}} D_t^{\alpha-1} \mathcal{W}(t) + \frac{\alpha^2 (\alpha - 1)^2}{2} (t - t_0 + r)^{\alpha-2} \\ &\quad \cdot {}^{\text{RL}} D_t^{\alpha-2} \mathcal{W}(t), \end{aligned} \quad (24)$$

for $t \geq t_0$.

On the other hand, it is not difficult to follow

$$\begin{aligned} \alpha^2 (t - t_0 + r)^{\alpha-1} {}^{\text{RL}} D_t^{\alpha-1} \mathcal{W}(t) &= \alpha^2 (t - t_0 + r)^{-(1-\alpha)} \\ &\quad \cdot {}^{\text{RL}} D_t^{-(1-\alpha)} \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\ &\leq \alpha^2 (t - t_0 + r)^{-(1-\alpha)} \frac{1}{\Gamma(1-\alpha)} \\ &\quad \times \sup_{-\tau \leq \theta \leq t} \left[\max \left\{ \frac{|e_i(\theta)|}{\beta_i}, i = 1, 2, \dots, n \right\} \right] \int_{t_0}^t (t - s)^{-\alpha} ds \\ &\leq \alpha^2 (t - t_0 + r)^{-(1-\alpha)} \frac{(t - t_0)^{1-\alpha}}{(1-\alpha) \Gamma(1-\alpha)} \\ &\quad \times \sup_{-\tau \leq \theta \leq t} \left[\max \left\{ \frac{|e_i(\theta)|}{\beta_i}, i = 1, 2, \dots, n \right\} \right] \end{aligned}$$

$$\begin{aligned}
&\leq \alpha^2 \left(\frac{t-t_0}{t-t_0+r} \right)^{1-\alpha} \frac{1}{\Gamma(2-\alpha)} \\
&\times \sup_{-\tau \leq \theta \leq t} \left[\max \left\{ \frac{|e_i(\theta)|}{\beta_i}, i = 1, 2, \dots, n \right\} \right] \leq \frac{\alpha^2}{\Gamma(2-\alpha)} \\
&\cdot \mathcal{W}(\tilde{\theta}) \leq \frac{\alpha^2}{r^\alpha \Gamma(2-\alpha)} \overline{\mathcal{V}}(t), \\
&\frac{\alpha^2 (\alpha-1)^2}{2} (t-t_0+r)^{\alpha-2} {}^{\text{RL}}_{t_0} D_t^{\alpha-2} \mathcal{W}(t) \\
&\leq \frac{\alpha^2 (\alpha-1)^2}{2} (t-t_0+r)^{\alpha-2} \frac{1}{\Gamma(2-\alpha)} \\
&\times \int_{t_0}^t (t-s)^{1-\alpha} \max \left\{ \frac{|e_i(s)|}{\beta_i}, i = 1, 2, \dots, n \right\} ds \\
&\leq \frac{\alpha^2 (\alpha-1)^2}{2} (t-t_0+r)^{\alpha-2} \\
&\times \frac{\sup_{-\tau \leq \theta \leq t} [\max \{|e_i(\theta)|/\beta_i, i = 1, 2, \dots, n\}]}{\Gamma(2-\alpha)} \\
&\cdot \int_{t_0}^t (t-s)^{1-\alpha} ds \leq \frac{\alpha^2 (\alpha-1)^2}{2} (t-t_0+r)^{\alpha-2} \\
&\times \frac{(t-t_0)^{2-\alpha} \sup_{-\tau \leq \theta \leq t} [\max \{|e_i(\theta)|/\beta_i, i = 1, 2, \dots, n\}]}{(2-\alpha) \Gamma(2-\alpha)} \\
&\leq \frac{\alpha^2 (\alpha-1)^2}{2} \left(\frac{t-t_0}{t-t_0+r} \right)^{2-\alpha} \\
&\times \frac{\sup_{-\tau \leq \theta \leq t} [\max \{|e_i(\theta)|/\beta_i, i = 1, 2, \dots, n\}]}{(2-\alpha) \Gamma(2-\alpha)} \\
&\leq \frac{\alpha^2 (\alpha-1)^2}{2} \\
&\cdot \frac{\sup_{-\tau \leq \theta \leq t} [\max \{|e_i(\theta)|/\beta_i, i = 1, 2, \dots, n\}]}{(2-\alpha) \Gamma(2-\alpha)} \\
&\leq \frac{\alpha^2 (\alpha-1)^2}{2r^\alpha (2-\alpha) \Gamma(2-\alpha)} \overline{\mathcal{V}}(t) \leq \frac{\alpha^2}{r^\alpha \Gamma(2-\alpha)} \overline{\mathcal{V}}(t),
\end{aligned} \tag{25}$$

for $t \geq t_0$, $\overline{\mathcal{W}}(t) = \mathcal{W}(\tilde{\theta})$, where $\tilde{\theta} \in [-\tau, t]$.

Substituting (25) into (24), it is obvious to derive that

$$\begin{aligned}
&{}^C_{t_0} D_t^\alpha \mathcal{V}(t) \\
&\leq (t-t_0+r)^\alpha {}^C_{t_0} D_t^\alpha \max \left\{ \frac{|e_i(t)|}{\beta_i}, i = 1, 2, \dots, n \right\} \\
&\quad + \frac{\Delta}{r^\alpha \Gamma(2-\alpha)} + \frac{\Theta}{r^\alpha \Gamma(1-\alpha)} \\
&= (t-t_0+r)^\alpha {}^C_{t_0} D_t^\alpha \mathcal{W}(t) + \frac{1+\alpha}{r^\alpha \Gamma(2-\alpha)} \overline{\mathcal{V}}(t),
\end{aligned} \tag{26}$$

where

$$\begin{aligned}
\Delta &= 2\alpha^2 \sup_{-\tau \leq \theta \leq t} \left[(\theta-t_0+r)^\alpha \right. \\
&\quad \cdot \max \left\{ \frac{|e_i(\theta)|}{\beta_i}, i = 1, 2, \dots, n \right\} \left. \right], \\
\Theta &= (1+2\alpha) \sup_{-\tau \leq \theta \leq t} \left[(\theta-t_0+r)^\alpha \right. \\
&\quad \cdot \max \left\{ \frac{|e_i(\theta)|}{\beta_i}, i = 1, 2, \dots, n \right\} \left. \right].
\end{aligned} \tag{27}$$

Utilizing (22), it is obvious that there exists a $\hat{k} \in \{1, 2, \dots, n\}$ such that

$$\mathcal{W}(t) = \frac{|e_{\hat{k}}(t)|}{\beta_{\hat{k}}}, \tag{28}$$

for $t \geq t_0$.

From (17), together with the data-sampling principle (21), we compute

$$\begin{aligned}
&{}^C_{t_0} D_t^\alpha \mathcal{W}(t) = \frac{1}{\beta_{\hat{k}}} {}^C_{t_0} D_t^\alpha |e_{\hat{k}}(t)| \leq \frac{1}{\beta_{\hat{k}}} \\
&\cdot \operatorname{sgn}(e_{\hat{k}}(t)) {}^C_{t_0} D_t^\alpha e_{\hat{k}}(t) \leq \frac{1}{\beta_{\hat{k}}} \operatorname{sgn}(e_{\hat{k}}(t)) \left[-d_{\hat{k}} e_{\hat{k}}(t) \right. \\
&\quad + \sum_{j=1}^n a_{\hat{k}j} g_j(e_j(t)) + \sum_{j=1}^n b_{\hat{k}j} f_j(e_j(t-\tau(t))) \\
&\quad \left. + \sum_{\ell=1}^m \sum_{h=1}^m \mathfrak{R}_{\ell h} \mathfrak{G}_{h\hat{k}} e_{\hat{k}}(t_k) \right] \leq -\frac{d_{\hat{k}} |e_{\hat{k}}(t)|}{\beta_{\hat{k}}} + \frac{1}{\beta_{\hat{k}}} \\
&\cdot \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j \frac{|e_j(t)|}{\beta_j} + \frac{1}{\beta_{\hat{k}}} \\
&\cdot \sum_{j=1}^n \beta_j |b_{\hat{k}j}| F_j \frac{|e_j(t-\tau(t))|}{\beta_j} + \frac{1}{\beta_{\hat{k}}} \\
&\cdot \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| |e_{\hat{k}}(t_k)| \leq - \left[d_{\hat{k}} \right. \\
&\quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right] \mathcal{W}(t) \\
&\quad + \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |b_{\hat{k}j}| F_j \overline{\mathcal{W}}(t-\tau(t)).
\end{aligned} \tag{29}$$

Then

$$\begin{aligned}
& (t - t_0 + r)^\alpha {}^C D_t^\alpha \mathcal{W}(t) \leq - (t - t_0 + r)^\alpha \left[d_{\hat{k}} \right. \\
& \quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right] \mathcal{W}(t) + (t \\
& \quad - t_0 + r)^\alpha \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |b_{\hat{k}j}| F_j \overline{\mathcal{W}}(t - \tau(t)) \leq - \left[d_{\hat{k}} \right. \\
& \quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right] \mathcal{V}(t) \\
& \quad + \frac{(t - t_0 + r)^\alpha}{\beta_{\hat{k}} (t - t_0 + r + \bar{\theta})^\alpha} \sum_{j=1}^n \beta_j |b_{\hat{k}j}| F_j \overline{\mathcal{V}}(t) \leq - \left[d_{\hat{k}} \right. \\
& \quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right. \\
& \quad \left. - \left(\frac{r}{r + \bar{\theta}} \right)^\alpha \sum_{j=1}^n \frac{\beta_j}{\beta_{\hat{k}}} |b_{\hat{k}j}| F_j \right] \mathcal{V}(t) \leq - \left[d_{\hat{k}} \right. \\
& \quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right. \\
& \quad \left. - \left(\frac{r}{r - \tau} \right)^\alpha \sum_{j=1}^n \frac{\beta_j}{\beta_{\hat{k}}} |b_{\hat{k}j}| F_j \right] \mathcal{V}(t), \quad (30)
\end{aligned}$$

where $\bar{\theta} \in [-\tau, t]$ such that $\overline{\mathcal{V}}(t) = (t - t_0 + \bar{\theta} + r)^\alpha \overline{\mathcal{W}}(t)$, when $\overline{\mathcal{V}}(t) = \mathcal{V}(t)$.

Substituting (30) into (26), we have

$$\begin{aligned}
& {}^C D_t^\alpha \mathcal{V}(t) \leq - \left[d_{\hat{k}} - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j \right. \\
& \quad \left. - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| - \left(\frac{r}{r - \tau} \right)^\alpha \sum_{j=1}^n \frac{\beta_j}{\beta_{\hat{k}}} |b_{\hat{k}j}| F_j \right] \\
& \quad \cdot \mathcal{V}(t) + \frac{1 + \alpha}{r^\alpha \Gamma(2 - \alpha)} \overline{\mathcal{V}}(t) \leq - \left[d_{\hat{k}} \right. \\
& \quad \left. - \frac{1}{\beta_{\hat{k}}} \sum_{j=1}^n \beta_j |a_{\hat{k}j}| G_j - \sum_{\ell=1}^m \sum_{h=1}^m |\mathfrak{R}_{\ell h}| |\mathfrak{G}_{h\hat{k}}| \right. \\
& \quad \left. - \left(\frac{r}{r - \tau} \right)^\alpha \sum_{j=1}^n \frac{\beta_j}{\beta_{\hat{k}}} |b_{\hat{k}j}| F_j - \frac{1 + \alpha}{r^\alpha \Gamma(2 - \alpha)} \right] \mathcal{V}(t), \quad (31)
\end{aligned}$$

when $\overline{\mathcal{V}}(t) = \mathcal{V}(t)$.

According to (20) and (31),

$${}^C D_t^\alpha \overline{\mathcal{V}}(t) \leq 0, \quad (32)$$

for all $t \geq t_0$.

By the definition of Caputo derivative, from (32), we can obtain

$$\frac{1}{\Gamma(1 - \alpha)} \frac{d}{dt} \int_{t_0}^t \frac{\overline{\mathcal{V}}(s)}{(t - s)^\alpha} ds \leq \frac{\overline{\mathcal{V}}(t_0)}{\Gamma(1 - \alpha)} (t - t_0)^{-\alpha}; \quad (33)$$

then

$$\overline{\mathcal{V}}(t) \leq \overline{\mathcal{V}}(t_0), \quad (34)$$

for $t \geq t_0$. Thus, for $i = 1, 2, \dots, n$,

$$\begin{aligned}
|e_i(t)| & \leq \beta_i \mathcal{W}(t) = \beta_i \frac{\mathcal{V}(t)}{(t - t_0 + r)^\alpha} \leq \beta_i \frac{\overline{\mathcal{V}}(t)}{(t - t_0 + r)^\alpha} \\
& \leq \beta_i \frac{\mathcal{V}(t_0)}{(t - t_0 + r)^\alpha} = \beta_i \frac{r^\alpha \overline{\mathcal{W}}(t_0)}{(t - t_0 + r)^\alpha} \\
& \leq \frac{\beta_i r^\alpha \|\psi\|_{\mathcal{E}}}{\beta_{\min} (t - t_0 + r)^\alpha}, \quad (35)
\end{aligned}$$

for $t \geq t_0$, where $\beta_{\min} = \min\{\beta_i, i = 1, 2, \dots, n\}$; then

$$\|e(t)\| \leq \frac{\Lambda r^\alpha \|\psi\|_{\mathcal{E}}}{(t - t_0 + r)^\alpha}, \quad (36)$$

where $\Lambda = (1/\beta_{\min}) \sum_{i=1}^n \beta_i$. Therefore, system (17) is globally $O(t^{-\alpha})$ stable, which implies that the drive-response-based coupled systems (5) and (7) can reach global $O(t^{-\alpha})$ synchronization.

Remark 6. In Theorem 5, (20) is an algebraic condition, which relies on only system parameters, free-weighting parameters r and β_i ($i = 1, 2, \dots, n$). Besides, (21) is used to characterize the sampling time point, which can be determined by trigger mechanism. Generally, the discrimination conditions in Theorem 5 can be easily rectified. In addition, although the results established are based on $0 < \alpha < 1$, clearly, such results can be also applied to $\alpha = 1$.

Remark 7. Aiming at the realistic environment under the limited bandwidth of communication channel, it is very critical to reduce the data transmission rate for networked systems. As (21), the centralized data-sampling mechanism for the sampling time point is an effective way, which does not waste the bandwidth of network to be with needless signals, and then reduces the data transmission and power consumption.

4. Two Illustrative Examples

In this section, two illustrative examples are given to demonstrate the effectiveness of theoretical criterion.

FIGURE 1: Chaotic behavior.

Example 1. Consider a two-dimensional neural network model (5) described by

$$\begin{aligned}
 \alpha &= 0.5, \\
 D &= \begin{pmatrix} 6 & 0 \\ 0 & 6 \end{pmatrix}, \\
 A &= \begin{pmatrix} 0.2 & 0.2 \\ 0.5 & 0.5 \end{pmatrix}, \\
 B &= \begin{pmatrix} 0.2 & 0.8 \\ 0.2 & 0.8 \end{pmatrix}, \\
 \tau(t) &= |\sin(t)|, \\
 I &= (0.5, 0.5)^T, \\
 C &= \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}, \\
 g(Y) &= f(Y) = \tanh(Y).
 \end{aligned} \tag{37}$$

Figure 1 shows simulation result of the above neural network model, which can exhibit chaotic behavior.

Obviously, we can obtain $G_1 = G_2 = 1$, $F_1 = F_2 = 1$, and $\tau = 1$; to apply Theorem 5, it requires

$$\begin{aligned}
 6 - \frac{1}{\beta_1} \sum_{j=1}^2 \beta_j |a_{1j}| - \sum_{\ell=1}^2 \sum_{h=1}^2 |\mathfrak{K}_{\ell h}| \\
 - \left(\frac{r}{r-1} \right)^{0.5} \sum_{j=1}^2 \frac{\beta_j}{\beta_1} |b_{1j}| - \frac{1.5}{r^{0.5} \Gamma(1.5)} \geq 0,
 \end{aligned}$$

FIGURE 2: Evolutive behavior of $x_1(t)$ and $\hat{x}_1(t)$.

$$\begin{aligned}
 6 - \frac{1}{\beta_2} \sum_{j=1}^2 \beta_j |a_{2j}| - \sum_{\ell=1}^2 \sum_{h=1}^2 |\mathfrak{K}_{\ell h}| \\
 - \left(\frac{r}{r-1} \right)^{0.5} \sum_{j=1}^2 \frac{\beta_j}{\beta_2} |b_{2j}| - \frac{1.5}{r^{0.5} \Gamma(1.5)} \geq 0.
 \end{aligned} \tag{38}$$

Select $r = 4$, $\beta_1 = 1$, $\beta_2 = 2$, and

$$K = \begin{pmatrix} \mathfrak{K}_{11} & \mathfrak{K}_{12} \\ \mathfrak{K}_{21} & \mathfrak{K}_{22} \end{pmatrix} = \begin{pmatrix} 0.6 & 0.6 \\ -0.6 & -0.6 \end{pmatrix}; \tag{39}$$

then (38) are satisfied, so the designed controller is

$$u(t) = K C e(t_k) = \begin{pmatrix} 1.2 & 1.2 \\ -1.2 & -1.2 \end{pmatrix} e(t_k), \tag{40}$$

$$t \in [t_k, t_{k+1}).$$

Figure 2 is utilized to show the simulation result for the master/drive system state $x_1(t)$ and the slave/response system state $\hat{x}_1(t)$ in Example 1. Figure 3 is utilized to show the simulation result for the master/drive system state $x_2(t)$ and the slave/response system state $\hat{x}_2(t)$ in Example 1. Clearly, the drive-response-based coupled systems in Example 1 can reach global $O(t^{-\alpha})$ synchronization. Figure 4 shows the centralized data-sampling release instants and the corresponding release intervals. These results via computer simulations nicely demonstrate that the designed controller performs very well.

FIGURE 3: Evolutive behavior of $x_2(t)$ and $\hat{x}_2(t)$.

Example 2. Consider a one-dimensional neural network model (5) described by

$$\begin{aligned}
 \alpha &= 0.5, \\
 D &= 6, \\
 A &= 1, \\
 B &= -3.5, \\
 \tau(t) &= |\sin(t)|, \\
 I &= 1, \\
 C &= 1, \\
 g(Y) &= f(Y) = \tanh(Y).
 \end{aligned} \tag{41}$$

Figure 5 shows simulation result of the above neural network model without any external control, which generates disorganized behavior.

Obviously, we can obtain $G = 1$, $F = 1$, and $\tau = 1$; to apply Theorem 5, it requires

$$D - |A| - |\mathfrak{K}| - \left(\frac{r}{r-1}\right)^{0.5} |B| - \frac{1.5}{r^{0.5}\Gamma(1.5)} \geq 0. \tag{42}$$

Select $r = 4$ and

$$K = \mathfrak{K} = 0.1; \tag{43}$$

then (42) is satisfied, so the designed controller is

$$u(t) = KCe(t_k) = 0.1e(t_k), \quad t \in [t_k, t_{k+1}). \tag{44}$$

Figure 6 is utilized to show the simulation result for the master/drive system state $x(t)$ and the slave/response system state $\hat{x}(t)$ in Example 2. Figure 7 shows the centralized data-sampling release instants and the corresponding release intervals. Such results via computer simulations also indicate that the designed controller performs very well.

FIGURE 4: Release instants and release intervals.

FIGURE 5: Disorganized behavior.

FIGURE 6: Evolutive behavior of $x(t)$ and $\hat{x}(t)$.

5. Conclusion

In this paper, the centralized data-sampling approach for global $O(t^{-\alpha})$ synchronization of fractional-order neural net-

FIGURE 7: Release instants and release intervals.

works with time delays is investigated. Some sufficient conditions for centralized data-sampling principle are derived and proved to guarantee the global $O(t^{-\alpha})$ synchronization for drive-response-based coupled neural networks. The proposed theoretical results are sufficient conditions for global $O(t^{-\alpha})$ synchronization and contain a lot of space for further improvement. Future research can be extended to (1) more economical and efficient event-triggered mechanism and (2) more realistic networked systems involving stochastic effect or incomplete measurement.

Competing Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

The work is supported by the Research Project of Hubei Provincial Department of Education of China under Grant T201412.

References

- [1] I. Ameen and P. Novati, "The solution of fractional order epidemic model by implicit Adams methods," *Applied Mathematical Modelling. Simulation and Computation for Engineering and Environmental Systems*, vol. 43, pp. 78–84, 2017.
- [2] A. Wu and Z. Zeng, "Global Mittag-Leffler stabilization of fractional-order memristive neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 1, pp. 206–217, 2017.
- [3] B. S. Chen and J. J. Chen, "Global $O(t^{-\alpha})$ stability and global asymptotical periodicity for a non-autonomous fractional-order neural networks with time-varying delays," *Neural Networks*, vol. 73, pp. 47–57, 2016.
- [4] J. Palanivel, K. Suresh, S. Sabarathinam, and K. Thamilmaran, "Chaos in a low dimensional fractional order nonautonomous nonlinear oscillator," *Chaos, Solitons & Fractals*, vol. 95, pp. 33–41, 2017.
- [5] N. Miljković, N. Popović, O. Djordjević, L. Konstantinović, and T. B. Šekara, "ECG artifact cancellation in surface EMG signals by fractional order calculus application," *Computer Methods and Programs in Biomedicine*, vol. 140, pp. 259–264, 2017.
- [6] S. Saha Ray and S. Sahoo, "Two efficient reliable methods for solving fractional fifth order modified Sawada-Kotera equation appearing in mathematical physics," *Journal of Ocean Engineering and Science*, vol. 1, no. 3, pp. 219–225, 2016.
- [7] K. Amoura, R. Mansouri, M. Bettayeb, and U. M. Al-Saggaf, "Closed-loop step response for tuning PID-fractional-order-filter controllers," *ISA Transactions*, vol. 64, pp. 247–257, 2016.
- [8] R. Rakkiyappan, G. Velmurugan, and J. Cao, "Finite-time stability analysis of fractional-order complex-valued memristor-based neural networks with time delays," *Nonlinear Dynamics*, vol. 78, no. 4, pp. 2823–2836, 2014.
- [9] R. Rakkiyappan, G. Velmurugan, and J. Cao, "Stability analysis of memristor-based fractional-order neural networks with different memductance functions," *Cognitive Neurodynamics*, vol. 9, no. 2, pp. 145–177, 2015.
- [10] R. Rakkiyappan, G. Velmurugan, and J. Cao, "Stability analysis of fractional-order complex-valued neural networks with time delays," *Chaos, Solitons and Fractals*, vol. 78, pp. 297–316, 2015.
- [11] D. K. Raju, B. S. Umre, A. Junghare, and B. C. Babu, "Mitigation of subsynchronous resonance with fractional-order PI based UPFC controller," *Mechanical Systems and Signal Processing*, vol. 85, pp. 698–715, 2017.
- [12] F. Wang, Y. Yang, M. Hu, and X. Xu, "State estimation for fractional-order neural networks," *Optik*, vol. 126, no. 23, pp. 4083–4086, 2015.
- [13] Y. Arya and N. Kumar, "BFOA-scaled fractional order fuzzy PID controller applied to AGC of multi-area multi-source electric power generating systems," *Swarm and Evolutionary Computation*, vol. 32, pp. 202–218, 2017.
- [14] A. Wu and Z. Zeng, "Boundedness, Mittag-Leffler stability and asymptotical ω -periodicity of fractional-order fuzzy neural networks," *Neural Networks*, vol. 74, pp. 73–84, 2016.
- [15] G. M. Mahmoud, M. E. Ahmed, and T. M. Abed-Elhameed, "On fractional-order hyperchaotic complex systems and their generalized function projective combination synchronization," *Optik*, vol. 130, pp. 398–406, 2017.
- [16] A. Wu, Z. Zeng, and X. Song, "Global Mittag-Leffler stabilization of fractional-order bidirectional associative memory neural networks," *Neurocomputing*, vol. 177, pp. 489–496, 2016.
- [17] R. Sharma, P. Gaur, and A. P. Mittal, "Design of two-layered fractional order fuzzy logic controllers applied to robotic manipulator with variable payload," *Applied Soft Computing*, vol. 47, pp. 565–576, 2016.
- [18] J. A. Gallegos and M. A. Duarte-Mermoud, "On the Lyapunov theory for fractional order systems," *Applied Mathematics and Computation*, vol. 287–288, pp. 161–170, 2016.
- [19] S. Zhang, Y. Yu, and H. Wang, "Mittag-Leffler stability of fractional-order Hopfield neural networks," *Nonlinear Analysis. Hybrid Systems*, vol. 16, pp. 104–121, 2015.
- [20] Q.-L. Han, "A discrete delay decomposition approach to stability of linear retarded and neutral systems," *Automatica*, vol. 45, no. 2, pp. 517–524, 2009.
- [21] Y. He, J. Zeng, M. Wu, and C.-K. Zhang, "Robust stabilization and H_∞ controllers design for stochastic genetic regulatory networks with time-varying delays and structured uncertainties," *Mathematical Biosciences*, vol. 236, no. 1, pp. 53–63, 2012.

- [22] H. Huang, T. Huang, and X. Chen, "Global exponential estimates of delayed stochastic neural networks with Markovian switching," *Neural Networks*, vol. 36, pp. 136–145, 2012.
- [23] J. Liang, Z. Wang, Y. Liu, and X. Liu, "State estimation for two-dimensional complex networks with randomly occurring nonlinearities and randomly varying sensor delays," *International Journal of Robust and Nonlinear Control*, vol. 24, no. 1, pp. 18–38, 2014.
- [24] D. Liu and Q. Wei, "Finite-approximation-error-based optimal control approach for discrete-time nonlinear systems," *IEEE Transactions on Cybernetics*, vol. 43, no. 2, pp. 779–789, 2013.
- [25] J. Lu, D. W. Ho, J. Cao, and J. Kurths, "Single impulsive controller for globally exponential synchronization of dynamical networks," *Nonlinear Analysis. Real World Applications*, vol. 14, no. 1, pp. 581–593, 2013.
- [26] A. Wu and Z. Zeng, "Output convergence of fuzzy neurodynamic system with piecewise constant argument of generalized type and time-varying input," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 12, pp. 1689–1702, 2016.
- [27] R. Wang, P. Shi, Z.-G. Wu, and Y.-T. Sun, "Stabilization of switched delay systems with polytopic uncertainties under asynchronous switching," *Journal of the Franklin Institute*, vol. 350, no. 8, pp. 2028–2043, 2013.
- [28] Z. Wang, B. Shen, H. Shu, and G. Wei, "Quantized H_∞ control for nonlinear stochastic time-delay systems with missing measurements," *Institute of Electrical and Electronics Engineers. Transactions on Automatic Control*, vol. 57, no. 6, pp. 1431–1444, 2012.
- [29] Z. Wang, H. Zhang, and B. Jiang, "LMI-based approach for global asymptotic stability analysis of recurrent neural networks with various delays and structures," *IEEE Transactions on Neural Networks*, vol. 22, no. 7, pp. 1032–1045, 2011.
- [30] H. G. Zhang, Z. S. Wang, and D. Liu, "A comprehensive review of stability analysis of continuous-time recurrent neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 7, pp. 1229–1262, 2014.
- [31] H. Li, "Event-triggered state estimation for a class of delayed recurrent neural networks with sampled-data information," *Abstract and Applied Analysis*, vol. 2012, Article ID 731453, 21 pages, 2012.
- [32] M. Abdelrahim, R. Postoyan, J. Daafouz, and D. Nesic, "Robust event-triggered output feedback controllers for nonlinear systems," *Automatica*, vol. 75, pp. 96–108, 2017.
- [33] A. Tanwani, C. Prieur, and M. Fiacchini, "Observer-based feedback stabilization of linear systems with event-triggered sampling and dynamic quantization," *Systems and Control Letters*, vol. 94, pp. 46–56, 2016.
- [34] A. Seuret, C. Prieur, S. Tarbouriech, and L. Zaccarian, "Event-triggered control via reset control systems framework," *IFAC-PapersOnLine*, vol. 49, no. 18, pp. 170–175, 2016.
- [35] N. K. Sharma and T. V. Sreenivas, "Event-triggered sampling using signal extrema for instantaneous amplitude and instantaneous frequency estimation," *Signal Processing*, vol. 116, pp. 43–54, 2015.
- [36] S. Dashkovskiy and S. Pavlichkov, "Constructive design of adaptive controllers for nonlinear MIMO systems with arbitrary switchings," *IEEE Transactions on Automatic Control*, vol. 61, no. 7, pp. 2001–2007, 2016.
- [37] A. A. Pyrkin and A. A. Bobtsov, "Adaptive controller for linear system with input delay and output disturbance," in *Proceedings of the 52nd IEEE Conference on Decision and Control (CDC '13)*, vol. 61, pp. 4229–4234, IEEE, Florence, Italy, December 2013.
- [38] J. E. Azzaro and R. A. Veiga, "Sliding mode controller with neural network identification," *IEEE Latin America Transactions*, vol. 13, no. 12, pp. 3754–3757, 2015.

Hindawi

Submit your manuscripts at
<https://www.hindawi.com>