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Exponential synchronization of delayed memristor-based chaotic neural networks via periodically intermittent control

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ABSTRACT

This paper investigates the exponential synchronization of coupled memristor-based chaotic neural networks with both time-varying delays and general activation functions. And here, we adopt nonsmooth analysis and control theory to handle memristor-based chaotic neural networks with discontinuous right-hand side. In particular, several new criteria ensuring exponential synchronization of two memristor-based chaotic neural networks are obtained via periodically intermittent control. In addition, the new proposed results here are very easy to verify and also complement, extend the earlier publications. Numerical simulations on the chaotic systems are presented to illustrate the effectiveness of the theoretical results.

1. Introduction

Memristor-based neural networks made of hybrid complementary metal–oxide–semiconductors have a very wide range of uses in bioinspired engineering (Cantley, Subramaniam, Stiegler, Chapman, & Vogel, 2012; Itoh & Chua, 2009; Kim, Sah, Yang, Roska, & Chua, 2012; Pershin & Di Ventra, 2010; Sharifiy & Banadaki, 2010). Memristor-based neural networks are well suited to characterize the nonvolatile feature of the memory cell because of hysteresis effects. The studies of memristor-based neural networks would benefit a number of important applications in neural learning circuits (Cantley et al., 2012; Itoh & Chua, 2009; Sharifiy & Banadaki, 2010), associative memories (Pershin & Di Ventra, 2010), new classes of artificial neural systems (Hu & Wang, 2010; Kim et al., 2012), and so on.

The memristor-based neural networks are a class of state-dependent nonlinear systems from a systems-theoretic point of view (Bao & Zeng, 2013; Chen, Zeng, & Jiang, 2014; Hu & Wang, 2010; Wen & Zeng, 2012; Wu, Wen, & Zeng, 2012; Wu & Zeng, 2012; Yang, Cao, & Yu, 2014; Zhang & Shen, 2013; Zhang, Shen, & Sun, 2012; Zhang, Shen, & Wang, 2013). Such a system can reveal coexisting solutions, jumped, transient chaos of rich and complex nonlinear behaviors, whereas, in the past decades, state-dependent nonlinear system has not received considerable attention. With the development and application of memristors, the studies of such state-dependent nonlinear system with its various generalizations may be an active area of research, to allow the memristors to be readily used in emerging technologies.

As is well known, chaos synchronization in nonlinear science has been known for a rather long time, and its applications to diverse areas such as secure communications and biological and chemical reactions. Since then, many important and fundamental results have been reported on the synchronization and control of chaotic systems, e.g, see Cao and Wan (2014), Liu (2009) and Liu, Wang, and Liu (2008). And many control approaches have been proposed to stabilize chaotic systems such as adaptive control (Zhang, Xie, Wang, & Zheng, 2007), feedback control (Zhu, Zhang, Fei, Zhang, & Li, 2009), impulsive control (Guan & Zhang, 2008; Sheng & Yang, 2008; Sun, Chen, Lu, & Chen, 2012), and intermittent control (Cai, Liu, Xu, & Shen, 2009; Hu, Yu, Jiang, & Teng, 2010a; Huang & Li, 2010; Huang, Li, & Liu, 2008; Huang, Li, Yu, & Chen, 2009; Yu, Hu, Jiang, & Teng, 2011).

Comparing with continuous control of chaos, the discontinuous control method, such as impulsive control and intermittent control, have received much interest because they are practical and easily implemented in engineering such as transportation and communication (Hu et al., 2010a; Huang, Li, Yu et al., 2009). The intermittent control is different from the impulsive control since impulsive control is activated only at some isolated instants, while intermittent control has a nonzero control width. In this scheme,

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the synchronization signals are used in the slave system at periodic time intervals (control width) when the slave system tracks the orbit of the driving system (Hu et al., 2010a; Huang et al., 2008; Huang, Li, Yu et al., 2009).

Moreover, to use intermittent control proves to be more cost effective than using control at all times (Amritkar & Gupte, 1993; Hu et al., 2010a; Huang, Li, Yu et al., 2009). After several decades, numerous studies with respect to intermittent control have been carried out (Hu, Yu, Jiang, & Teng, 2010b; Huang, Li, & Han, 2009; Li & Cao, 2014; Li, Feng, & Liao, 2007; Li, Liao, & Huang, 2007; Xia & Cao, 2009; Yang & Cao, 2009). However, on the synchronization of memristor-based chaotic neural networks via intermittent control, few results are found in the literature. On the other hand, the memristor-based chaotic neural networks with discontinuous right-hand side, this problem brings challenges to investigate the exponential synchronization of the systems via intermittent control.

Recently, Bao, Liu, & Xu (2010a, 2010b) show that the memristor-based chaotic system is more safe in secure communications. Therefore, using intermittent control to get synchronization of memristor-based chaotic neural networks is also more safe in secure communications, because intermittent control is the discontinuous control method, which can increase the difficulty when capturing the information by sending a periodic signal.

Motivated by the above discussions, in this paper, we will derive several new criteria ensuring exponential synchronization of memristor-based chaotic neural networks with both time-varying delays and general activation functions via periodically intermittent control.

The main advantages of this paper lie in the following aspects. Firstly, the dynamic analysis here adopts nonsmooth analysis and control theory to handle memristor based neural networks with discontinuous right-hand side. Secondly, periodically intermittent controller technique, which is totally different from the techniques employed in Bao and Zeng (2013), Chen et al. (2014), Hu and Wang (2010), Wen and Zeng (2012), Wu et al. (2012), Wu and Zeng (2012), Yang et al. (2014), Zhang et al. (2012), Zhang et al. (2013) and Zhang and Shen (2013) is to study the addressed neural networks in the paper. Thirdly, as the generalization of the obtained results, exponential synchronization of addressed neural networks under various feedback functions are discussed in detail. Lastly, some new criteria are derived to ensure synchronization of the neural networks, and the new proposed results here are very easy to verify and they achieve a valuable improvement, and also complement, and extend the earlier publications.

The organization of this paper is as follows. Some preliminaries are introduced in Section 2. In Section 3, some new criteria for the exponential synchronization are derived by using nonsmooth analysis and control theory. And then, numerical simulations are given to demonstrate the effectiveness of the proposed approach in Section 4. Finally, our conclusion is given in Section 5.

2. Preliminaries

In this paper, based on the previous works (Chen et al., 2014; Hu et al., 2010b; Wu et al., 2012; Zhang & Shen, 2013), we consider a class of memristor-based neural networks with time-varying delays as follows:

$$\begin{aligned}\frac{\mathrm{d}x_i(t)}{\mathrm{d}t} &= -x_i(t) + \sum_{j=1}^{n} a_{ij}(x_j(t))f_j(x_j(t)) \\ &\quad + \sum_{j=1}^{n} b_{ij}(x_j(t-\tau_j(t)))g_j(x_j(t-\tau_j(t))) + I_i, \\ &\quad t \geq 0,\ i \in N, \end{aligned}\tag{1}$$

where

$$a_{ij}(x_j(t)) = \frac{\mathbf{M}_{ij}}{\mathbf{C}_i} \times \mathrm{sgn}_{ij},$$

$$b_{ij}(x_j(t-\tau_j(t))) = \frac{\mathbf{W}_{ij}}{\mathbf{C}_i} \times \mathrm{sgn}_{ij}$$

where $\mathrm{sgn}_{ij} = 1$, if $i \neq j$ holds, otherwise, -1. $\mathbf{M}_{ij}$ and $\mathbf{W}_{ij}$ denote the memductances of memristors $\mathbf{R}_{ij}$ and $\widehat{\mathbf{R}}_{ij}$, respectively. In addition, $\mathbf{R}_{ij}$ represents the memristor between the neuron activation functions $f_j(x_j(t))$ and $x_i(t)$, $\widehat{\mathbf{R}}_{ij}$ represents the memristor between the neuron activation functions $g_j(x_j(t-\tau_j(t)))$ and $x_i(t)$. And $a_{ij}(x_j(t))$, $b_{ij}(x_j(t-\tau_j(t)))$ are memristors synaptic connection weights, denote the strengths of the jth unit on the ith unit at time t and time $t-\tau_j(t)$, respectively. $f_j, g_j : \mathbb{R} \to \mathbb{R}$ denotes the neuron activation functions, $\tau_j(t)$ corresponds to the transmission delays and satisfies $0 \leq \tau_j(t) \leq \tau$, $\dot{\tau}_j(t) \leq \sigma_0 < 1$ ($\tau > 0$, σ_0 is a constant), I_i is an external constant input, $i, j \in N$, $N = 1, 2, \ldots, n$.

As we know, capacitor $\mathbf{C}_i$ is changeless, memductances $\mathbf{M}_{ij}$ and $\mathbf{W}_{ij}$ respond to changes in pinched hysteresis loops. Thus, $a_{ij}(x_j(t))$, $b_{ij}(x_j(t-\tau_j(t)))$ will change, as pinched hysteresis loops change (Hu & Wang, 2010; Wen & Zeng, 2012; Wu et al., 2012; Wu & Zeng, 2012; Zhang et al., 2012, 2013). According to the feature of the memristor and the current–voltage characteristic, then

$$a_{ij}(x_j(t)) = \begin{cases} a_{ij}^{*}, & |x_j(t)| \leq T_j, \\ a_{ij}^{**}, & |x_j(t)| > T_j, \end{cases}$$

$$b_{ij}(x_j(t-\tau_j(t))) = \begin{cases} b_{ij}^{*}, & |x_j(t-\tau_j(t))| \leq T_j, \\ b_{ij}^{**}, & |x_j(t-\tau_j(t))| > T_j, \end{cases}$$

in which switching jumps $T_j > 0$, $a_{ij}^{*}, a_{ij}^{**}, b_{ij}^{*}, b_{ij}^{**}$, $i, j \in N$, are all constant numbers.

Throughout this paper, we consider system (1) as the drive system and corresponding response system is as follows:

$$\begin{aligned}\frac{\mathrm{d}y_i(t)}{\mathrm{d}t} &= -y_i(t) + \sum_{j=1}^{n} a_{ij}(y_j(t))f_j(y_j(t)) \\ &\quad + \sum_{j=1}^{n} b_{ij}(y_j(t-\tau_j(t)))g_j(y_j(t-\tau_j(t))) \\ &\quad + I_i + u_i(t), \quad t \geq 0,\ i \in N, \end{aligned}\tag{2}$$

where $i, j \in N$,

$$a_{ij}(y_j(t)) = \begin{cases} a_{ij}^{*}, & |y_j(t)| \leq T_j, \\ a_{ij}^{**}, & |y_j(t)| > T_j, \end{cases}$$

$$b_{ij}(y_j(t-\tau_j(t))) = \begin{cases} b_{ij}^{*}, & |y_j(t-\tau_j(t))| \leq T_j, \\ b_{ij}^{**}, & |y_j(t-\tau_j(t))| > T_j, \end{cases}$$

and $u_i(t)$ is a periodically intermittent controller which is defined by

$$u_i(t) = \begin{cases} \displaystyle\sum_{j=1}^{n} \omega_{ij}(y_j(t) - x_j(t)), & mT \leq t \leq mT + \delta, \\ 0, & mT + \delta < t \leq (m+1)T, \end{cases}\tag{3}$$

where $m = 0, 1, 2, \ldots$, and ω_{ij} are constants for all $i, j \in N$, which denote the control gains, T denotes the control period and $0 < \delta < T$ is called the control width.

In this paper, solutions of all systems considered in the following are intended in Filippov's sense (Filippov, 1988). We define $\|\phi\| = \sup_{-\tau \leq t \leq 0}[\sum_{i=1}^{n} |\phi_i(t)|^p]^{1/p}$, where p is a constant and $p \geq 1$, for $\forall \phi = (\phi_1(t), \phi_2(t), \ldots, \phi_n(t)) \in \mathbb{C}([-\tau, 0], \mathbb{R}^n)$, $\mathrm{co}\{\underline{\xi}_i, \overline{\xi}_i\}$ denotes the convex hull of $\{\underline{\xi}_i, \overline{\xi}_i\}$. $\underline{a}_{ij} = \min\{a_{ij}^{*}, a_{ij}^{**}\}$, $\overline{a}_{ij} = \max\{a_{ij}^{*}, a_{ij}^{**}\}$, $\underline{b}_{ij} = \min\{b_{ij}^{*}, b_{ij}^{**}\}$, $\overline{b}_{ij} = \max\{b_{ij}^{*}, b_{ij}^{**}\}$. For