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Exponential adaptive synchronization of stochastic memristive chaotic recurrent neural networks with time-varying delays ☆

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ABSTRACT

This paper is focused on the global exponential adaptive synchronization problem of two stochastic memristive chaotic neural networks with both stochastic disturbance and time-varying delays. First, in order to develop the guaranteed cost control, a periodically alternate adaptive rule is designed. Then, by constructing appropriate Lyapunov–Krasovskii functionals, several easily verified synchronization criteria are derived to guarantee exponential adaptive synchronization of drive-response stochastic memristive chaotic recurrent neural networks. Lastly, a numerical simulation is carried out to demonstrate the effectiveness of the proposed results.

1. Introduction

For the last few years, as we all know that neural networks has been extensively researched to solve various engineering issues such as control, optimization, image processing, function approximation, associative memory design, pattern recognition, and so on [1,2]. Time delays are ubiquitou because the limited speed of signal transmission and the limited switching speed of neurons and amplifiers. In addition, the synaptic transmission in neural networks is a noisy process brought by stochastic disturbance. And both time delays and stochastic disturbance can result in poor performance or instability of networks. Therefore, the dynamical behaviors of neural networks can be heavily influenced by stochastic disturbance and time delays. Note that there have existed lots of results of synchronization/stability of neural networks subject to stochastic disturbance and/or time delays [3–5].

As we all know that in conventional hardware realization of artificial neural networks, the joint weights are usually implemented by means of resistors [6], floating gate transistors [7] or CMOS [8]. However, it is known that the disadvantages of these approaches are as follows: the problems of hard real-time weights variation, nonlinearity in synaptic weighting, and power-consuming weight storage, respectively [9]. In the meantime, it is worth noting that the large size of very large-scale hardware implementation of joint weights is a big bottleneck too.

Fortunately, in 1971, the memristors were theoretically predicted by Prof. Chua as the fourth fundamental electrical circuit element [10]. Memristors are nonvolatile memory nanoscale devices, whose resistances slowly change depending on quantity of passing electric charge by supplying a voltage or current, This is similar to biological synapses. Similar devices by various materials have been illustrated to show memristive behaviors [11,12] and the memristors have aroused the greatest interest in realizing synapses and joint weights in cellular neural networks and other kinds of artificial neural networks [13–19], ever since the advent of the novel circuit prototype of memristor, a two-terminal titanium dioxide nanoscale device successfully obtained by the Hewlett–Packard research team [20,21]. Recently, the memristive chaotic recurrent neural networks have been studied widely and successfully applied in neural learning circuits [22,23], pattern recognition [24], feature extraction [25], and so on.

It should be pointed out that, memristive chaotic recurrent neural networks are modeled as differential equations, whose right-hand side are discontinuous. And, there have exited lots of solution notions to deal with systems with discontinuous right-hand side, such as Krasovskii solutions [26] and Filippov solutions [27].

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Under the framework of Filippov's solution, which is easier to handle systems with discontinuous right-hand side, we here adopts set-valued maps and differential inclusions theory to deal with memristive chaotic recurrent neural networks with discontinuous right-hand side.

On the other hand, the adaptive chaos synchronization of neural networks is of great practical significance, and has attracted much attention recently for its a number of potential applications include various science and engineering fields like biological technology [28–31], information science [4,32–35] and secure communication [36–38]. Therefore, It is very imperative to study the adaptive chaos synchronization of the memristive chaotic recurrent neural networks, e.g., in [39], by employing a ω-matrix measure method and Filippov's discontinuous theory, the authors study the periodicity and synchronization of the coupled memristive neural networks with supremums and delays. In the existing literature, many synchronization methods have been proposed such as impulsive control [40–43], pinned control [32,36], feedback control [44,45], adaptive control [4,46], intermittent control [47–50] and so on. Meanwhile, adaptive control method is an effective way for neural networks to obtain an appropriate control gain, which guarantees the synchronization of neural networks. However, to the best of our knowledge, the global exponential synchronization problem of drive-response stochastic memristive chaotic neural networks with both stochastic disturbance and time-varying delays via periodically alternate adaptive control has received very little research attention.

Motivated by the above discussions, the drive-response exponential synchronization problem of stochastic memristive recurrent neural networks under alternate adaptive control is investigated in this paper. Our main contributions are highlighted as follows: First, a novel periodically alternate adaptive control rule is proposed for investigating the exponential synchronization for drive-response memristive recurrent neural networks. Second, we build a new mathematical model of memristive recurrent neural networks with both stochastic disturbance and time-varying delays. Third, a basic assumption in existing references is removed and through constructing an appropriate Lyapunov–Krasovskii functional, some novel sufficient conditions are proposed to guarantee that two stochastic memristive chaotic recurrent neural networks with both stochastic disturbance and time-varying delays achieve exponential synchronization.

This paper is organised as follows. In Section 2, the model description and preliminaries are introduced. In Section 3, some exponential adaptive synchronization criteria of two memristive recurrent neural networks with both stochastic disturbance and time-varying delays are derived. Then, a numerical simulation is carried out to demonstrate the effectiveness of the theoretic results in Section 4. Finally, Section 5 draw some conclusions.

Notations. Throughout this paper, $\mathbb{N}^+$ and $\mathbb{N}$ denote the set of positive integers and the set of nonnegative integers, respectively. $\mathbb{R}$ and $\mathbb{R}^n$ denote the set of real numbers and the n-dimensional space, respectively. For vector $x \in \mathbb{R}^n$, $|x|$ and x^{T} denote the Euclidean norm and its transpose, respectively. $\mathbb{R}^{n\times n}$ denotes $n\times n$ real matrix. $co\{\underline{\zeta},\overline{\zeta}\}$ denotes the convex hull of $\{\underline{\zeta},\overline{\zeta}\}$. $d_i^+ = \max\{|d_i|, |\overline{d}_i|\}$, $a_{ij}^+ = \max\{|\underline{a}_{ij}|, |\overline{a}_{ij}|\}$, and $b_{ij}^+ = \max\{|\underline{b}_{ij}|, |\overline{b}_{ij}|\}$. $PC([t_0-\tau, t_0], \mathbb{D})$ denotes the family of piecewise continuous function from $[t_0-\tau, t_0]$ into $\mathbb{D}\subseteq\mathbb{R}^n$ with the norm $\|\phi\|_\tau = \max_{1\le i\le n}\{\sup_{-\tau\le t\le 0}|\phi_i(t)|\}$, where $\phi = (\phi_1(t), \phi_2(t), \ldots, \phi_n(t))^{\mathrm{T}}$.

2. Model description and preliminaries

In this paper, considering the following mathematical model of stochastic memristive delayed neural network as the drive system

$$
\begin{aligned}
dx_i(t) =& \Big[-d_i x_i(t) + \sum_{j=1}^{n} a_{ij}(x_i(t)) f_j(x_j(t)) \\
&+ \sum_{j=1}^{n} b_{ij}(x_i(t)) g_j(x_j(t-\tau_{ji}(t))) + J_i\Big]dt \\
&+ \sigma_i(t, x_i(t), x_i(t-\tau_i(t)))d\omega_i(t), \quad t\in(0,+\infty). \qquad (1)
\end{aligned}
$$

in which $x_i(t)\in\mathbb{R}$ denotes the voltage of the capacitor, $d_i>0$, $a_{ij}(x_i(t))$ and $b_{ij}(x_i(t))$ denote the memristive synaptic connection weights, respectively. $f_j(\cdot)$ and $g_j(\cdot)$ are activation functions, $\tau_{ji}(t)$ and $\tau_i(t)$ represent the transmission time-varying delays, J_i is an external input or bias, $\sigma_i(t, x_i(t), x_i(t-\tau_i(t)))$ is the noise intensity and $(\omega_1(t), \omega_2(t), \ldots, \omega_n(t))^{\mathrm{T}}$ represent the scalar standard Brownian motions, which is defined on $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}, \mathcal{P})$, $i = 1, 2, \ldots, n$, and

$$
a_{ij}(x_i(t)) = \begin{cases} a_{ij}^*, & |x_i(t)| < \Upsilon_i, \\ a_{ij}^{**}, & |x_i(t)| > \Upsilon_i, \end{cases}
$$

$$
b_{ij}(x_i(t)) = \begin{cases} b_{ij}^*, & |x_i(t)| < \Upsilon_i, \\ b_{ij}^{**}, & |x_i(t)| > \Upsilon_i, \end{cases}
$$

where $i, j = 1, 2, \ldots, n$, $\Upsilon_i > 0$ is the switching jumps; a_{ij}^*, a_{ij}^{**}, b_{ij}^* and b_{ij}^{**} are all the constants.

The initial conditions of (1) is $x_i(s) = \varphi_i(s), s\in[-\tau_M, 0]$, in which $\varphi(s) = (\varphi_1(s), \varphi_2(s), \ldots, \varphi_n(s))^{\mathrm{T}} \in PC([-\tau_M, 0], \mathbb{R}^n)$, $i = 1, 2, \ldots, n$.

The corresponding response system is described by the following differential equation form

$$
\begin{aligned}
dy_i(t) =& \Big[-d_i y_i(t) + \sum_{j=1}^{n} a_{ij}(y_i(t)) f_j(y_j(t)) \\
&+ \sum_{j=1}^{n} b_{ij}(y_i(t)) g_j(y_j(t-\tau_{ji}(t))) + J_i + u_i\Big]dt \\
&+ \sigma_i(t, y_i(t), y_i(t-\tau_i(t)))d\omega_i(t), \quad t\in(0,+\infty). \qquad (2)
\end{aligned}
$$

where $i = 1, 2, \ldots, n$, $u(t) = (u_1(t), u_2(t), \ldots, u_n(t))^{\mathrm{T}}$ denotes a periodically alternate adaptive controller, and

$$
a_{ij}(y_i(t)) = \begin{cases} a_{ij}^*, & |y_i(t)| < \Upsilon_i, \\ a_{ij}^{**}, & |y_i(t)| > \Upsilon_i, \end{cases}
$$

$$
b_{ij}(y_i(t)) = \begin{cases} b_{ij}^*, & |y_i(t)| < \Upsilon_i, \\ b_{ij}^{**}, & |y_i(t)| > \Upsilon_i, \end{cases}
$$

The initial conditions of model (2) is $y_i(s) = \phi_i(s), s\in[-\tau, 0]$, in which $i = 1, 2, \ldots, n$ and $\phi(s) = (\phi_1(s), \phi_2(s), \ldots, \phi_n(s))^{\mathrm{T}} \in PC([t_0-\tau, t_0], \mathbb{R}^n)$.

In this paper, making three assumptions to establish our main results as follows:

Assumption 1. The noise intensity $\sigma_i(t, x_i(t), x_i(t-\tau_i(t))$ satisfies $\sigma_i(t, 0, 0) = 0$, and

$$
\begin{aligned}
&|\sigma_i(t, x_i(t), x_i(t-\tau_i(t))) - \sigma_i(t, y_i(t), y_i(t-\tau_i(t)))|^2 \\
&\le \xi_i|x_i(t)-y_i(t)|^2 + \zeta_i|x_i(t-\tau_i(t)) - y_i(t-\tau_i(t))|^2,
\end{aligned}
$$

where ξ_i, ζ_i are all nonnegative constants and $i = 1, 2, \ldots, n$.

Assumption 2. The activation functions $f_i(\cdot)$ and $g_i(\cdot)$ are monotone nondecreasing.

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