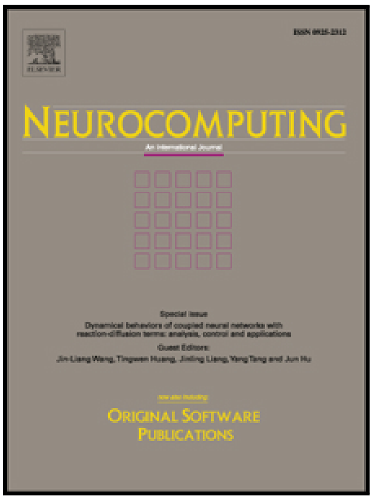

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Exponential stability criteria for delayed second-order memristive neural networks

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Abstract

This brief presents a class of delayed second-order memristive neural networks (SMNNs). By building a new Lyapunov functional and employing some inequalities technique, we derive some new criteria ensuring global exponential stability of the delayed SMNNs. Compared with other researches on dynamics of neural networks (NNs), our system is described by second-order differential equations and memristor. In addition, we discuss the SMNNs directly and the main results given here without changing the SMNNs into the first-order differential systems. Finally, simulations are given to elaborate the validity of the obtained criteria.

Keywords: Exponential stability; Neural networks; Memristor; Time delays

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1. Introduction

In these years, neural networks (NNs) have been successfully applied to numerous fields such as associative memory, optimization problems, signal processing and fault diagnosis [1-4]. These applications are closely related with the dynamical properties of NNs. As we know, stability is a part of dynamical properties, and stability of NNs is also a prerequisite for its applications. Therefore, the studies on stability of NNs are necessary and many good results have been given, e.g., see [2,4].

On the other hand, due to various reasons, time delays inevitably exist in engineering [2], biological systems [5] and other nonlinear systems. In NNs, because of the finite switching speed of amplifier circuits, time delays also unavoidably exist. Time delay may lead to instability or other poor performance of NNs. So, the researches on stability of NNs with time delays are important and have been extensively reported in [2,4].

NNs with an inertial term, of course, is also a kind of NNs. Inertial NNs has evident biological and engineering backgrounds [6], and its dynamical behaviors has been proved more complex [7]. Compared to conventional NNs with first order derivative of states, inertial NNs are second order derivative of states, little attention has been given to such system. Up to now, only several papers have been found about inertial NNs. The exponential stability of delayed inertial NNs was considered in [8,9]. The periodic solutions of inertial bi-directional associative memory neural networks were presented in [10]. In 2014, based on matrix measure method and inequality techniques, Cao and Wan [11] studied the synchronization problem of inertial NNs. In 2017, Li, Li and Hu [12] got some sufficient conditions to ascertain the asymptotic synchronization of the inertial NNs by using feedback control strategy and without reduced-order method. With the application of inertial NNs to the fields such as associative memory, signal processing and optimization problems, the studies of such second-order differential system are valuable.

Memristive neural networks (MNNs) are today's hot topics and there are many works for relevant aspects in the publications [13-18]. More recently, MNNs with inertial term are proposed and investigated in [10,19-24]. The method in those existing works are all through reduced-order, that's, by changing the second-order memristive neural networks (SMNNs) into the first-order system, the reduced-order method expand the dimension of the SMNNs, which increase the difficulty of the theoretical analysis for the SMNNs.

In this brief, based on the previous works [19], we will study the delayed SMNNs as follows:

$$\frac{\mathrm{d}^2 v_i(t)}{\mathrm{d}t^2} = -\alpha_i v_i(t) - D_i(v_i(t))\frac{\mathrm{d}v_i(t)}{\mathrm{d}t} + \sum_{j=1}^{n} A_{ij}(v_i(t))w_j(v_j(t)) + \sum_{j=1}^{n} B_{ij}(v_i(t))w_j(v_j(t-h_j(t))),\ \ t \geq 0, i \in \mathcal{M}, \qquad (1)$$

where

$$D_i(v_i(t)) = \frac{1}{\mathbf{C}_i}\Big[\sum_{j=1}^{n}\Big(\frac{1}{\mathbf{M}_{ij}} + \frac{1}{\mathbf{W}_{ij}}\Big)\theta_{ij} + \frac{1}{\mathbf{R}_i}\Big],$$

$$A_{ij}(v_i(t)) = \frac{\theta_{ij}}{\mathbf{C}_i\mathbf{M}_{ij}}, B_{ij}(v_i(t)) = \frac{\theta_{ij}}{\mathbf{C}_i\mathbf{W}_{ij}}, \alpha_i = \frac{1}{\mathbf{C}_i\mathbf{L}_i}.$$

here $\theta_{ij} = 1$, if $i \neq j$ holds, otherwise, -1. $v_i(t)$ is the state of the i-th neuron at time t, $\mathbf{M}_{ij}$ and $\mathbf{W}_{ij}$ denote the memristors. $D_i(v_i(t))$ is the i-th neuron self-inhibitions at time t, and $A_{ij}(v_i(t)), B_{ij}(v_i(t))$ are memristors synaptic connection weights. $h_j(t)$ corresponds to the transmission delays and satisfies $0 \leq h_j(t) \leq h, \dot{h}_j(t) \leq h_0 < 1$. $\mathbf{R}_i$ and $\mathbf{C}_i$ are the resistor and capacitor, $\mathbf{L}_i$ is inductance, $i, j \in \mathcal{M} = \{1, 2, ..., n\}$. Here, Fig. 1 was given and which provide an evident engineering background of the system (1).

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