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Research article

Passivity analysis of memristor-based impulsive inertial neural networks with time-varying delays

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ABSTRACT

This paper focuses on delay-dependent passivity analysis for a class of memristive impulsive inertial neural networks with time-varying delays. By choosing proper variable transformation, the memristive inertial neural networks can be rewritten as first-order differential equations. The memristive model presented here is regarded as a switching system rather than employing the theory of differential inclusion and set-value map. Based on matrix inequality and Lyapunov-Krasovskii functional method, several delay-dependent passivity conditions are obtained to ascertain the passivity of the addressed networks. In addition, the results obtained here contain those on the passivity for the addressed networks without impulse effects as special cases and can also be generalized to other neural networks with more complex pulse interference. Finally, one numerical example is presented to show the validity of the obtained results.

1. Introduction

Memristor was proposed by Chua [1] and the archetype of the memristor was first come true by Hewlett-Packard Lab team on nanotechnology [2,3]. The memristor is a nonlinear circuit component and its value named memductance (or memristance) is not unique. Recent developments in the simulation of diverse types of memristors have been rapidly translated into studying of memristive neural networks. The mathematical model of memristive neural networks is expressed as an implicit differential equation with discontinuous right side. In order to analyze the class of discontinuous differential equations, most works adopt the theory of differential inclusion and set-valued map, which has become a standard mathematical tool in analysing dynamic behaviors of memristive neural networks [4–7].

Meanwhile, most of the existed results for researching the dynamic systems are acquired in the light of Lyapunov-Krasovskii functional approach. According to the theory of Lyapunov-Krasovskii functional techniques, it is a critical factor to judge whether the conservatism of delay-dependent criteria are better or not. To obtain less conservative conclusions, it must be understood that the reason why the conservative property of the Lyapunov-Krasovskii functional technique occurs. In general, the construction of Lyapunov-Krasovskii functional and the bound of the derivative of the time-varying delay are two main norms. Hence, it is very important for constructing a proper Lyapunov-Krasovskii functional to get the less conservative results. To structure an appropriate Lyapunov-Krasovskii functional, there are usually two ways: one is to divide the delay into many sections in the constructed Lyapunov-Krasovskii functional and another is to add some delay terms to the states in the created Lyapunov-Krasovskii functional. At present, it is still an outstanding issue how to construct a suitable Lyapunov-Krasovskii functional. Besides, it is also a great challenge how to obtain less conservative results by constructing new Lyapunov-Krasovskii functional and effectively applying inequality techniques.

For another, various practical systems such as queue management system [8], input-affine systems [9], networked systems [10,11] and T-S fuzzy systems [12–14] are nonlinear systems with complex dynamical behaviors. It is extremely difficult to study dynamical behaviors of these nonlinear systems. To be noted that the passivity theory is effective and robust in the investigation the problem of dynamical behaviors, especially for stability analysis of nonlinear systems, since the intrinsic quality of the passivity theory is that the passivity of a system can retain the system internal stability. Recently, considerable attention has been paid to the different passivity analysis for neural networks [15–18]. The passivity has been studied for various memristive neural networks with or without time delays [19–27].

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In 1986, Babcock and Westervelt [28] showed that the dynamics could be complex when the neuron couplings contain an inertial nature. Wheeler and Schieve [29] first proposed a second order (third order) inertial neural network model and discussed its stability, bifurcation, chaos phenomenon. In Ref. [30], the Hopf bifurcation and bifurcation direction of a class of coupled neural network have been studied via the center manifold theorem and the perturbation scheme. In Refs. [31,32], the Lyapunov exponential stability of inertial Cohen-Grossberg-type neural networks was studied by inequality technique and analysis method. The authors [33] investigated the globally exponential stability of inertial BAM neural networks using homeomorphism theory and inequality technique and gave the sufficient condition in form of LMIs. In Ref. [34], the sufficient conditions guaranteeing exponential stability of impulsive inertial BAM neural networks were obtained by employing the comparison principle and the Lyapunov functional method. The author [35] presented sufficient conditions of exponential stability of anti-periodic solutions of inertial BAM neural networks. Cao and Wan [36] studied stability and synchronization of inertial BAM neural network with time delays via matrix measure method. By employing matrix measure and inequality techniques, Tu et al. investigated the dissipativity for inertial neural networks with time-varying delays and parameter uncertainties [37] and Lagrange exponential stability of inertial neural networks with time-varying delays [38], respectively. Wang and Tian [39] studied the global Lagrange stability of inertial neural networks with mixed time-varying delays. In Ref. [40], the global dissipativity for memristor-based inertial networks with time-varying delay of neutral type was investigated. R. Rakkiyappan et al. [41] researched stability and pinning synchronization of a class of inertial memristive neural networks with delay by using matrix measure.

In addition, impulsive effects widely exist in various fields such as chemical technology, population dynamics and economics, where the state is changed abruptly at certain moments of time. Therefore, impulsive neural network model belong to new category of dynamical systems, which are neither continuous nor discrete ones. It is necessary to think of the character of neural networks with impulsive effect, such as stability, periodicity and passivity. In Refs. [42–44], the authors have considered the stability of memristive neural networks with both impulsive effect and time-delays. The authors [45] analysed the global exponential convergence of impulsive inertial neural networks. In Ref. [46], the exponential stabilization was studied for complex-valued inertial neural networks with time-varying delays via impulsive control. The authors [47] analyzed the global exponential stability of inertial memristor-based neural networks with impulses and time-varying delays. However, to the best of our knowledge, there is hardly any paper that considered the passivity for memristor-based impulsive inertial neural networks with time-varying delays. This constitutes the motivation for the current study.

Motivated by the above analysis, The main purpose of this paper is to study the delay-dependent passivity for memristive impulsive inertial neural networks with time-varying delays. Under a class of general activation functions, it is the first attempt to study the passivity analysis of memristive impulsive inertial neural networks with time-varying delays. Meanwhile, instead of the theory of differential inclusion and set-value mapping which are used in Refs. [4–7,19–23,42–44], the parameters in this paper are divided into 2^n cases, which is more reasonable. Besides, the conditions are represented as matrix inequalities which can be efficiently solved via Matlab LMI Toolbox, which overcomes the shortcomings of the results based on algebraic inequalities [18]. It is worth pointing out that the passivity conditions of memristive impulsive inertial neural networks here include those of the models without impulsive effects as special cases. In a way, it is easy to mention that the memristive models in this paper contain the models in Refs. [23,24,34,36–38,41,45] as special cases. Finally, one numerical example is given to illustrate the effectiveness of the proposed results.

The remaining paper is organized as follows: Section 2 describes some preliminaries including a necessary definition and a lemma. The main results are obtained in Section 3. Section 4 presents a numerical example to confirm the validity of our results and concluding remarks are presented in Section 5.

2. Preliminaries

Throughout this paper, the superscript Q^T stands for the transpose of matrix Q. $Q > 0 (Q < 0)$ shows that the matrix Q is symmetric positive definite (negative definite). R^n denotes n-dimensional Euclidean space. $*$ indicates the symmetric elements. Let $\Gamma = \{1, 2, \ldots, n\}$.

Consider the following memristive inertial neural network with time-varying delays

$$\begin{cases} \dfrac{d^2x_i(t)}{dt^2} = -a_i(x_i(t))\dfrac{dx_i(t)}{dt} - b_i(x_i(t))x_i(t) + \displaystyle\sum_{j=1}^{n} c_{ij}(x_i(t))f_j(x_j(t)) \\ \qquad + \displaystyle\sum_{j=1}^{n} d_{ij}(x_i(t))f_j(x_j(t-\tau_j(t))) + u_i(t), \\ z_i(t) = f_i(x_i(t)), \end{cases} \tag{1}$$

for $i \in \Gamma$, where $x_i(t)$ is the state of the ith neuron, time delay $\tau_j(t)$ is differential and meets $0 \le \tau_j(t) \le \tau$, $\dot{\tau}_j(t) \le \mu < 1$. $u_i(t)$ denotes external input, $f_j(\cdot)$ is the neuron activation function and satisfies $f_j(0) = 0$. $z_i(t)$ is the ith output of network (1). $a_i(x_i(t))$ and $b_i(x_i(t))$ are the self-feedback connection memristor-based weight, $c_{ij}(x_i(t))$ and $d_{ij}(x_i(t))$ represent memristive synaptic weights, and

$$a_i(x_i(t)) = \begin{cases} \hat{a}_i, |x_i(t)| \le \vartheta_i, \\ \check{a}_i, |x_i(t)| > \vartheta_i, \end{cases} \qquad b_i(x_i(t)) = \begin{cases} \hat{b}_i, |x_i(t)| \le \vartheta_i, \\ \check{b}_i, |x_i(t)| > \vartheta_i, \end{cases}$$

$$c_{ij}(x_i(t)) = \begin{cases} \hat{c}_{ij}, |x_i(t)| \le \vartheta_i, \\ \check{a}_{ij}, |x_i(t)| > \vartheta_i, \end{cases} \qquad d_{ij}(x_i(t)) = \begin{cases} \hat{d}_{ij}, |x_i(t)| \le \vartheta_i, \\ \check{d}_{ij}, |x_i(t)| > \vartheta_i. \end{cases}$$

From the above definition, $a_i(x_i(t))$, $b_i(x_i(t))$, $c_{ij}(x_i(t))$ and $d_{ij}(x_i(t))$ are changed according to the state of the system and the connection weight switches between two different constants, i.e., $a_i(x_i(t))$ may be $\hat{a}_i$ or $\widehat{a}_i$, similarly, $b_i(x_i(t))$, $c_{ij}(x_i(t))$ and $d_{ij}(x_i(t))$ also have two choices, respectively.

For some chosen scalar $\xi_i \in R$, let variable transformation:

$$y_i(t) = \frac{dx_i(t)}{dt} + \xi_i x_i(t). \tag{2}$$

The network (1) can be written as

$$\begin{cases} \dfrac{dx_i(t)}{dt} = -\xi_i x_i(t) + y_i(t), \\ \dfrac{dy_i(t)}{dt} = -\beta_i(t)y_i(t) + \alpha_i(t)x_i(t) + \displaystyle\sum_{j=1}^{n} c_{ij}(t)f_j(x_j(t)) \\ \qquad + \displaystyle\sum_{j=1}^{n} d_{ij}(t)f_j(x_j(t-\tau_j(t))) + u_i(t), \\ z_i(t) = f_i(x_i(t)), \end{cases} \tag{3}$$

where $\alpha_i(t) = \beta_i(t)\xi_i - b_i(t)$, $\beta_i(t) = a_i(t) - \xi_i$.

Let $x(t) = (x_1(t), x_2(t), \ldots, x_n(t))^T$, $\Lambda = \mathrm{diag}\{\xi_1, \xi_2, \ldots, \xi_n\}$, $y(t) = (y_1(t), y_2(t), \ldots, y_n(t))^T$, $A(t) = \mathrm{diag}\{\alpha_1(t), \alpha_2(t), \ldots, \alpha_n(t)\}$, $B(t) = \mathrm{diag}\{\beta_1(t), \beta_2(t), \ldots, \beta_n(t)\}$, $C(t) = (c_{ij}(t))_{n\times n}$, $D(t) = (d_{ij}(t))_{n\times n}$, $u(t) = (u_1(t), u_2(t), \ldots, u_n(t))^T$, $z(t) = (z_1(t), z_2(t), \ldots, z_n(t))^T$, $\tau(t) =$

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