Neural Networks 88 (2017) 125–133

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

2017 Special Issue

Global dissipativity of memristor-based neutral type inertial neural networks☆

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ARTICLE INFO

Article history:
Available online 3 February 2017

Keywords:
Inertial neural networks
Dissipativity
Neutral
Memristor

ABSTRACT

The problem of global dissipativity for memristor-based inertial networks with time-varying delay of neutral type is investigated in this paper. Based on a proper variable substitution, the inertial system is transformed into a conventional system. Some sufficient criteria are established to ascertain the global dissipativity for the aforementioned inertial neural networks by employing analytical techniques and Lyapunov method. Meanwhile, the globally exponentially attractive sets and positive invariant sets are also presented here. Finally, numerical examples and simulations are given out to corroborate the effectiveness of obtained results.

1. Introduction

Since Hopfield neural network was implemented by the integrated circuit in 1984, many scholars paid their attention to investigate the dynamical characteristics and applications of neural networks with great enthusiasm (Abe, 1993; Berezansky, Braverman, & Idels, 2014; Cao & Wang, 2005; Rakkiyappan, Lakshmanan, Sivasamy, & Lim, 2016a; Zeng, Wang, & Liao, 2003). A comprehensive review for recurrent neural network has been presented in Zhang, Wang, and Liu (2014). The adaptive control problem for uncertain nonaffine nonlinear system with input saturation has been discussed with neural networks (Esfandiari, Abdollahi, & Talebi, 2015). The global exponential stability of delayed complex-valued neural networks with impulsive effects was investigated in Song, Yan, Zhao, and Liu (2016). In addition, the dynamics of some practical systems not only depend on the delay of state but also relies on the delay of state derivative, and such systems are called as neutral systems. They are frequently encountered in many fields such as population ecology, automatic control, and heat exchange, etc. (Brayton, 1966; Kuang, 1993). Lakshmanan, Senthilkumar, and Balasubramaniam (2011) gave out the robust stability analysis for delayed neutral systems with nonlinear perturbations by virtue of convex combination and integral inequalities techniques. By constructing Lyapunov functional, the global stability for a class of neutral neural systems was discussed (Arik, 2014). Based on nonnegative system, the stability problem for a class of linear time-varying neutral systems was discussed as well (Mazenc, 2015). The global Lagrange stability of delayed neutral neural networks with delays was considered in Jian and Wang (2015) and Luo, Zeng, and Liao (2011).

Compared to attention given to neural networks with first-order derivative of states, little attention has been given to the inertial neural networks. However, it also has great significance to consider neural network with inertial item as the inertial item can be viewed as powerful tool for generating bifurcation phenomenon and chaos (Babcock & Westervelt, 1986; Xing, Li, & Shu, 2012). Actually, there exist evident engineering and biological backgrounds for bringing an inertial term into a neural system.

☆ This work was jointly supported by the National Natural Science Foundation of China under Grant nos. 61573096,61272530, and 11601047, the "333 Engineering" Foundation of Jiangsu Province of China under Grant no. BRA2015286, the Scientific and Technological Research Program of Chongqing Municipal Education Commission under Grant no. KJ1501002, Natural Science Foundation Project of CQ (cstc2016jcyjA0596).

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http://dx.doi.org/10.1016/j.neunet.2017.01.004
0893-6080/

For example, it has been proved that the membrane of a hair cell can be realized by equivalent circuits with an inductance in semicircular canals of certain animals (Angelaki & Correia, 1991; Ashmore & Attwell, 1985). Scholars have proved that the charge or flux q of an electron element with inertial can be inertial with the tendency to be unchanged (Wang et al., 2010). And it has been proved that the dynamical behaviors would be more complex when the inertial item is introduced into neural networks (Babcock & Westervelt, 1986). The existence and stability analysis for periodic solutions of inertial bi-directional associative memory(BAM) neural networks were presented in Ke and Miao (2013) and Zhang, Li, Huang, and Tan (2015). Song and Xu considered the problem of stability as well as Bogdanov–Takens bifurcation for inertial coupling system, and some interesting results were obtained (Song & Xu, 2014). Based on matrix measure method and inequality techniques, the exponential stability and synchronization problem of inertial neural network were studied (Cao & Wan, 2014). The exponential stability of delayed inertial BAM neural networks was considered by using impulsive control (Qi, Li, & Huang, 2015). Some sufficient conditions were established in the terms of linear matrix inequalities to ascertain the coupled reaction–diffusion inertial neural networks to be synchronized (Dharani, Rakkiyappan, & Park, 2016).

As it is pointed out in Liao and Wang (2003), the dissipativity is a generalization of Lyapunov stability, and the dissipative theory can offer an effective framework for stability analysis. Moreover, it also builds strong connections among physics, control engineering and system theory, and it has been applied to norm estimation, chaos, and robust control, etc. Increasing scholars have paid their attention to the dissipativity analysis of system (Song & Zhao, 2005; Wang, She, Zhong, & Cheng, 2016; Wang, Zhang, & Ding, 2015; Wu, Li, & Huang, 2011; Wu, Shi, Su, & Chu, 2013). Some sufficient criteria ascertaining the global dissipativity for delayed neural network were presented in the form of linear matrix inequality (Cao, Yuan, Ho, & Lam, 2006). Based on Filippov solutions, the problem of dissipativity and quasi-synchronization of neural networks with time delay and discontinuous activations have been considered (Liu, Chen, Cao, & Lu, 2011). The global dissipativity analysis for T-S fuzzy neural networks with interval delays was discussed in Muralisankar, Gopalakrishnan, and Balasubramaniam (2012). Stochastic dissipativity for discrete-time neural networks was considered in Song (2011). By using Filippov theory and M-matrix, the authors considered the global dissipativity for neural networks with time delay and discontinuous functions (Duan & Huang, 2014).

In 1971, base on the completeness of variable statistic and symmetry of circuit variables, Professor Chua predicted the existence of the fourth fundamental circuit element called as memristor (abbreviation of memory resistor), which depicts the relation between the charge and flux (Chua, 1971). He also pointed out that the memristor could not be replaced by the other three elements: capacitor, resistor and inductor. However, the memristor failed to attract much attention from scholars until its prototype was realized by the research team of Hewlett–Packard Lab in 2008 (Strukov, Snider, Stewart, & Williams, 2008; Tour & He, 2008). The value of memristor is called memristance which not only depends on the polarity and magnitude of voltage applied on it, but also depends on the time duration. When the voltage is turned off, the memristance maintains on the most recent value until the voltage is turned on. It has been found that memristor devices possess some potential applications, for example, the service life of phone battery will be extended greatly and synapsis behaviors can be simulated by memristor devices. Based on memristors, the powerful brain like computer may be realized. When resistors in neural networks are replaced by memristors, memristor-based neural networks are conceived. And memristive networks not only persist the properties as conventional neural network, but also possess some peculiar properties, which make memristive neural networks with better applications, such as, imitating the human brain. Recently, the dynamics analysis of memristive neural network has become a hot topic of research (Li & Cao, 2015; Wang, Li, Huang, & Duan, 2013; Wu & Zeng, 2012; Yang, Cao, & Yu, 2014; Yang, Guo, & Wang, 2015; Zhang & Shen, 2013, 2014). The global stability and stabilization of memristive neural networks were discussed (Wang et al., 2013; Zhang & Shen, 2014). The problem of synchronization for memristor-based neural networks was also investigated (Li & Cao, 2015; Wu, Wen, & Zeng, 2012; Yang, Cao, & Qiu, 2015; Yang et al., 2014; Zhang & Shen, 2013). And several easy-checked criteria were provided in Cao and Li (2017) to ascertain the fixed-time synchronization for delayed memristor-based neural networks. By employing control theory and non-smooth analysis, Wu and Zeng studied the Lagrange stability for delayed memristor-based neural network (Wu & Zeng, 2014). The global dissipativity for memristor-based neural networks was also investigated in Guo, Wang, and Yan (2013) and Li, Rakkiyappan, and Velmurugan (2015). The stability analysis for delayed memristive complex-valued neural networks was implemented in Rakkiyappan, Velmurugan, Rihan, and Lakshmanan (2016b).

As far as we know, the problem of global dissipativity for memristor-based inertial neural networks with neutral delays is challenging and still open. We will attempt to do some effort to shorten the gap. The main contributions of our paper can be summed up as follows:

(i) The circuit implementation of inertial neural networks with time delay is given out.
(ii) The memristor-based neural network with both inertial item and neutral delay is considered, and there are few literatures if none discussed the system. Moreover, the activation function discussed here is not only nonlinear but also unbounded.
(iii) We consider the global dissipativity which is a generalization of Lyapunov stability. And the sufficient criteria obtained here can guarantee globally exponentially dissipative. Moreover, the sufficient criteria are easy to be checked by MATLAB.
(iv) $\dot{x}(t)$ is introduced into the Lyapunov functional, and a new Lyapunov functional is proposed.

The remainder of the paper is arrayed as follows: Model description and preliminaries are placed in Section 2. The main results are exhibited and proved in Section 3. Two numerical examples and simulations are given out to verify effectiveness of our results in Section 4. In Section 5, some conclusions and future research topics are presented.

Notations: In this paper, R^n represents the n-dimensional Euclidean space. Let E be appropriate dimension identity matrix and A^T be the transpose of matrix A. $|A| = (|a_{ij}|)_{n\times n}$. For a matrix, $*$ represents the symmetric elements in a symmetric matrix. $\mathbb{N}^* = \{1, 2, \ldots, n\}$. $C([-\tau, 0]; R^n)$ denotes a class of continuous mapping set from $[-\tau, 0]$ to R^n. $A \prec 0$ means that A is a negative definite matrix. For $\varphi \in C([-\tau, 0]; R^n)$, $\|\varphi\| \triangleq \sup_{-\tau\le s\le 0} \|\varphi(s)\|$. $x \in R^n \setminus \Omega$ means $x \in R^n$ but $x \notin \Omega$. Ω_ε is the ε-neighborhood of Ω.

2. Preliminaries

Firstly, we provide the circuit of inertial neural networks in Fig. 1 such that the inertial neural network can be well understood. Based on Kirchhoff's current law, the equation of the ith subsystem