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Anti-synchronization of complex-valued memristor-based delayed neural networks

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Abstract

This paper investigates the anti-synchronization of complex-valued memristor-based neural networks with time delays via designed external controllers. By constructing appropriate Lyapunov functions and using inequality technique, two different types of controllers are derived to guarantee the exponential anti-synchronization of complex-valued memristor-based delayed neural networks. Compared with existing relevant results, the proposed results of this paper are more general and less conservative. In addition, the presented theoretical results are easy to be checked with the parameters of systems themselves. Finally, an example with numerical simulations illustrates the effectiveness of the obtained results.

Keywords: Complex-valued neural networks, Memristor, Anti-synchronization, Controller design.

1. Introduction

For the past few decades, the dynamical behaviors of nonlinear systems have attracted the attention of many researchers and many interesting results have been reported (Zhu, Yang, & Shen, 2016; Zhu & Shen, 2013; Sheng, Shen, & Zhu, 2016; Sheng, Zhang, & Zeng, 2017; Fu, Ma, & Chai, 2015; Cao & Wang, 2005; Chen, Chai, Wu, & Yang, 2012; Di Marco, Forti, Grazzini, & Pancioni, 2012; Huang, Li, Duan, & Starzyk, 2012). Among these, the study on neural networks becomes particularly important due to the vast potential applications in automation, pattern recognition, image processing, sensing signal processing, business forecasting, data mining and so on (Sheng, Zhang, & Zeng, 2017; Fu, Ma, & Chai, 2015; Cao & Wang, 2005; Chen, Chai, Wu, & Yang, 2012; Di Marco, Forti, Grazzini, & Pancioni, 2012).

As we all know, researchers proposed the artificial neural networks based on the modern neuroscience. Although they reflect the basic characteristics of human brain, the natural neural networks are still difficult to be truly described. One of reason is that resistor does not possess memory function just as neuronal synapse. So, it would be better if scientists can find a new circuit element with memory characteristic to replace resistor. With the introduction and invention of memristor (as a contraction of memory and resistor) (Chua, 1971; Strukov, Snider, Stewart, & Williams, 2008; Tour & He, 2008), conventional resistors are successfully replaced with memristors in artificial neural networks. It is worth mentioning that memristor can play an important role to transmit information between neurons just like synapse, which can better simulate the human brain. Therefore, researchers taken the memristor-based connection weights into consideration in model to build a class of memristor-based neural networks, which are a class of state-dependent switching nonlinear systems. In recent years, there are many excellent theoretical results about the dynamical analysis of memristor-based neural networks have been proposed, such as exponential stability (Zhang, Huang, He, & Li, 2017; Chen, Zeng, & Jiang, 2014; Wang, Duan, Li, Wang, & Huang, 2017), input-to-state stability (Wu & Zeng, 2014a), Lagrange stability (Wu & Zeng, 2014b, 2014c), dissipativity (Tu, Cao, Alsaadi, & Alsaadi, 2017; Li & Cao, 2015), passivity analysis (Wen, Zeng, Huang, & Chen, 2013; Guo, Wang, & Yan, 2014), synchronization control (Zhang & Shen, 2013a; Yang, Luo, Liu, & Li, 2017; Yang & Ho, 2016; Zhang & Shen, 2015), anti-synchronization control (Wang, Li, Peng, Wang, Kurth, Xiao, & Yang, 2016; Wu & Zeng; 2013; Zhang & Shen, 2013b), finite-time stability (Wang & Shen, 2012).

It is easy to find that the above studies lie in the situation of real-valued neural networks. And we know that real-valued dynamical systems have been applied in various fields, but they, too, have some inherent limitations. For instance, the detection of symmetry problem and XOR problem can be solved by a single complex-valued neuron with the orthogonal decision boundaries, but a single real-valued neuron fails to do so. Thus, it is necessary to investigate the dynamics of complex-valued neural networks. Complex-valued neural networks have complex-valued states, activation functions and connection weights, hence, it has very different and more complicated dynamical behaviors than real-valued ones. The dynamical analysis of complex-valued neural networks has attracted so much attention of researchers in recent years (Rakkiyappan, Cao, & Velmurugan, 2015; Hu & Wang, 2015a, 2015b; Liu & Chen, 2016; Rakkiyappan, Velmurugan, & Cao, 2014; Zhou & Song, 2013; Fang & Sun, 2015; Zhang, Lin,

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