Neural Networks 98 (2018) 203–211

Contents lists available at ScienceDirect

Neural Networks

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

Fixed-time stabilization of impulsive Cohen–Grossberg BAM neural networks

Hongfei Li [a], Chuandong Li [a,*], Tingwen Huang [b], Wanli Zhang [a]

[a] Chongqing Key Laboratory of Nonlinear Circuits and Intelligent Information Processing, College of Electronic and Information Engineering, Southwest University, Chongqing 400715, PR China
[b] Department of Mathematics, Texas A & M University at Qatar, Qatar

ARTICLE INFO

Article history:
Received 21 June 2017
Received in revised form 15 November 2017
Accepted 21 November 2017
Available online 2 December 2017

Keywords:
Cohen–Grossberg neural networks
Impulses
Fixed-time stability
Stabilization
BAM neural networks

ABSTRACT

This article is concerned with the fixed-time stabilization for impulsive Cohen–Grossberg BAM neural networks via two different controllers. By using a novel constructive approach based on some comparison techniques for differential inequalities, an improvement theorem of fixed-time stability for impulsive dynamical systems is established. In addition, based on the fixed-time stability theorem of impulsive dynamical systems, two different control protocols are designed to ensure the fixed-time stabilization of impulsive Cohen–Grossberg BAM neural networks, which include and extend the earlier works. Finally, two simulations examples are provided to illustrate the validity of the proposed theoretical results.

1. Introduction

Impulsive dynamical systems can be viewed as a subclass of hybrid systems and comprised of three parts, i.e., a continuous-time subsystem, which governs the evolution of the system between impulsive or resetting events; a difference equation, which describes the way the state of the system are instantaneously jumped; and a switching criterion which determines the impulse moments. The dynamic behaviors of impulsive dynamical systems have been studied extensively in the aforementioned work, such as stability, consensus, synchronization and stabilization (Amato, De Tommasi, & Pironti, 2013; Bai, 2008; He, Qian, & Cao, 2017; Huang, Li, Duan, & Starzyk, 2012; Kartsatos, 2005; Li, O'Regan, & Akca, 2015; Li & Wu, 2016; Nersesov & Haddad, 2008; Qiu, Sun, Yang, et al., 2017; Yang & Lu, 2016).

As well known that bidirectional associative memory (BAM) neural networks were originally introduced by Kosko (1988), which generalized the single-layer auto associative Hebbian correlator to a two-layer pattern-matched hetero associative circuit. Nowadays, the dynamics analysis especially stability analysis for BAM neural networks has become an attractive research topic due to their potential application in pattern recognition, automatic control and image processing (Liu, Jiang, Cao, Wang, & Wang, 2013; Rajivganthi, Rihan, Lakshmanan, & Muthukumar, 2016). In Liu et al. (2013), a continuous stabilizator was designed for stabilizing the states of stochastic BAM neural networks in finite time, and then, the finite-time stabilization for a class stochastic BAM neural networks with parameter uncertainties was considered. In Rajivganthi et al. (2016), authors studied the finite-time stability for a class of fractional-order Cohen–Grossberg BAM neural networks with time delays by using differential mean value theorem and contraction mapping principle. In 1983, Cohen and Grossberg firstly proposed a neural network model (Cohen & Grossberg, 1983), which is called Cohen–Grossberg neural networks. The mathematical properties of this model have received increasing interest, such as finite-time stability, synchronization, stabilization and periodic solution (Cai & Huang, 2017; Cohen & Grossberg, 1983; Rajivganthi et al., 2016). For instance, the paper Cai and Huang (2017) investigated the finite-time synchronization of discontinuous Cohen–Grossberg neural networks with mixed time-delays via state-feedback control.

Note that the finite-time stability, as an important field of stability analysis, are studied extensively (Amato, Ariola, & Cosentino, 2010; Amato et al., 2013; Cai & Huang, 2017; Cohen & Grossberg, 1983; Ghasemi & Nersesov, 2014; Ghasemi, Nersesov, & Clayton, 2014; Liu, Cao, Yu, & Song, 2016; Liu et al., 2013; Nersesov & Haddad, 2008; Qiu et al., 2017; Rajivganthi et al., 2016; Sun, Yun, & Li, 2017; Wang, Zou, Zuo, & Li, 2016; Yang & Lu, 2016). Especially, one of the important problem of finite-time stability analysis is the estimation of the settling time. The settling time heavily depends on the initial conditions of the system, in other words, different

* Corresponding author.
E-mail address: licd@cqu.edu.cn (C. Li).

https://doi.org/10.1016/j.neunet.2017.11.017
0893-6080/

settling times depend on different initial states. However, in many practical environment, the knowledge of initial conditions of many research systems such as robotics, smart grids, vehicle monitoring, physical models, may be hardly accurately obtained, or impossible to be obtained in advance, which leads to the poor estimation of the settling time. To overcome this drawback, a new concept called the fixed-time stability was introduced by Polyakov (2012), if the system is globally finite-time stable and the settling time function is bounded for any initial values, that is to say, the convergence time is regardless of the initial states. Following this route to handle fixed-time stability, many new approaches and results were obtained (He, Ho et al., 2017; Hu, Yu, Chen, Jiang, & Huang, 2017; Liu & Chen, 2016; Liu, Yu, Wang, et al., 2017; Lu, Liu, & Chen, 2016; Ni, Liu, Liu, Hu, & Li, 2017; Polyakov, 2012; Polyakov, Efimov, & Perruquetti, 2015; Wan, Cao, Wen, & Yu, 2016; Wang, Wu, Huang, Ren, & Wu, 2016; Yang, Lam, Ho, et al., 2017; Zuo, 2014). For example, Polyakov (2012) provided global fixed-time stability of the closed-loop system by two types of nonlinear control algorithms, and allowed to adjust a guaranteed settling time independently on initial conditions. In Hu et al. (2017), the authors presented a new theorem of fixed-time stability by virtue of reductio ad absurdum, and the high-precision estimation of the settling-time was obtained. It was shown that the estimation bound of the settling time was less conservative and more accurate compared with the previous results. The paper Ni et al. (2017) proposed a fast fixed-time nonsingular terminal sliding mode control method and applied it to design static var compensator controller for chaos suppression in power systems. In Yang et al. (2017), the authors introduced the fixed-time synchronization of complex networks with impulsive effects by designing a new Lyapunov function and constructing comparison systems.

Motivated by the above analysis, a large number of papers have considered the finite-time stability and stabilization problem of impulsive dynamical control systems (Amato et al., 2013; Nersesov & Haddad, 2008; Qiu et al., 2017; Yang & Lu, 2016), and a great deal of results of fixed-time stability and synchronization for coupled neural networks and coupled complex networks have been obtained (He, Ho et al., 2017; Hu et al., 2017; Liu & Chen, 2016; Liu et al., 2017; Lu et al., 2016; Ni et al., 2017; Polyakov, 2012; Polyakov et al., 2015; Wan et al., 2016; Wang, Wu et al., 2016; Zuo, 2014). Compared with the existing results about fixed-time stability behavior, there are very few results to deal with fixed-time stability of impulsive dynamical system (Yang et al., 2017), due to the dynamical complexity of the impulsive dynamical systems and lacking of the theory of fixed-time stability of impulsive dynamical systems.

To summarize, the paper mainly has the following contribution: (1) This paper addresses the problem of fixed-time stability analysis of impulsive dynamical systems. By using a novel constructive approach based on some comparison techniques for differential inequalities, some sufficient conditions are derived to guarantee the fixed-time stability of impulsive dynamical systems. It is worth noting that the complexity caused by impulsive disturbance makes it difficult for us to study the fixed-time stability property of system. As the impulse effects is introduced to the neural networks, the fixed-time stability analysis for the cannot be studies with same routine as to the conventional neural network without impulses. Therefore, a new theorem of fixed-time stability for impulsive dynamical systems is established. (2) The fixed-time stability property for impulsive dynamical system is a new concept. In this paper, the convergence time of fixed-time stability is regardless of the initial states. Furthermore, the bound of setting-time can be estimated in advance without depending on any initial conditions but only depending on the designed scalars. Compared with existing works about some finite-time stability behaviors of impulsive dynamical systems (Amato et al., 2013; Nersesov & Haddad, 2008; Qiu et al., 2017; Yang & Lu, 2016), it is easy to see that fixed-time stability is more appropriate to solve many real control problems. (3) This paper discusses the impulse effects, making the study of fixed-time stabilization property more challenging. Based on the proposed theoretical results, it is proved that the impulsive Cohen–Grossberg BAM neural networks are fixed-time stable at the equilibrium point under two different types of control protocols. Two numerical results are presented to illustrate the validity of the proposed theoretical analysis.

The structure of this paper is as follows. In Section 2, model description and some necessary definitions, lemma, assumptions are presented. In Section 3, based on comparison principle and a power integrator analysis method, a new fixed-time stability theorem for impulsive dynamical systems is established. Besides, based on the theorem results, two different controllers are designed to ensure the fixed-time stabilization of impulsive Cohen–Grossberg BAM neural networks, which include and extend the earlier works. In Section 4, two numerical simulations are provided to illustrate the effectiveness of the theoretical analysis. Finally, Some conclusions about future research are discussed in Section 5.

2. Model formulation and preliminaries

Consider the following impulsive Cohen–Grossberg BAM neural networks:

$$\begin{cases} \dot{x}_i(t) = -d_i(x_i(t))\Big\{a_i(x_i(t)) - \sum_{j=1}^{m} b_{ij}f_j(y_j(t)) - I_i\Big\}, \\ \quad t \neq t_k, \quad t \in \mathbb{R}_+, \\ \dot{y}_j(t) = -h_j(y_j(t))\Big\{c_j(y_j(t)) - \sum_{i=1}^{n} d_{ji}g_i(x_i(t)) - J_j\Big\}, \\ \quad t \neq t_k, \quad t \in \mathbb{R}_+, \\ \Delta x_i|_{t=t_k} = -q_i x_i(t_k), \quad k \in \mathbb{N}, \\ \Delta y_j|_{t=t_k} = -\rho_j y_j(t_k), \quad k \in \mathbb{N}, \end{cases} \tag{1}$$

for $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$; $\mathbb{N}$ denotes the sets of positive integers, and $\mathbb{R}_+$ denotes nonnegative real numbers. $x_i(t)$ denotes the state vectors of the ith neurons at time t in X-layer; $y_j(t)$ denotes the state vectors of the jth neurons at time t in Y-layer; respectively, $d_i(x_i(t))$ represents the amplification function of the ith neuron in X-layer; $h_j(y_j(t))$ represents the amplification function of the jth neuron in Y-layer; $a_i(x_i(t))$ and $c_j(y_j(t))$ denote appropriately behaved functions; b_{ij} represents the connection weight of the jth neuron in Y-layer to the ith neuron in X-layer; d_{ji} represents the connection weight of the ith neuron in X-layer to the jth neuron in Y-layer; $f_j(y_j(t))$ denotes the neuron activation function of the jth neuron in X-layer; $g_i(x_i(t))$ denotes the neuron activation function of the ith neuron in Y-layer; I_i and J_j denote the neuron of an external input on the ith neuron in X-layer and on the jth neuron in Y-layer. For all $k \in \mathbb{N}$, $\Delta x_i(t_k) = x_i(t_k^+) - x_i(t_k)$, in which $x_i(t_k^+) = \lim_{t \to t_k+0} x_i(t)$, denotes the state jumps at the impulse instants t_k; $\Delta y_j(t_k) = y_j(t_k^+) - y_j(t_k)$, in which $y_j(t_k^+) = \lim_{t \to t_k+0} y_j(t)$, denotes the state jumps at the impulse instants t_k. Without loss of generalization, throughout this paper we assume that $x_i(t_k^-) = \lim_{t \to t_k-0} x_i(t) = x_i(t_k)$, i.e., the solution $x_i(t)$ is left continuous at impulse point; $y_j(t_k^-) = \lim_{t \to t_k-0} y_j(t) = y_j(t_k)$, i.e., the solution $y_j(t)$ is left continuous at impulse point. q_i and ρ_j are said impulsive control constants. The impulsive sequence $\{t_k\}_{k\in\mathbb{N}}$ satisfies $0 \le t_0 < t_1 < \cdots < t_k < \cdots$, $\lim_{k\to+\infty} t_k = +\infty$.

Throughout this paper, for simplicity, $\mathbb{R}$ denotes the sets of real numbers. Moreover, $\mathbb{R}^{n+m}$ denotes the $n + m$ dimensional real spaces. Let $x(t) = (x_1(t), x_2(t), \ldots, x_n(t))^T$,