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Impulsive synchronization of stochastic reaction–diffusion neural networks with mixed time delays

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ABSTRACT

This paper discusses impulsive synchronization of stochastic reaction–diffusion neural networks with Dirichlet boundary conditions and hybrid time delays. By virtue of inequality techniques, theories of stochastic analysis, linear matrix inequalities, and the contradiction method, sufficient criteria are proposed to ensure exponential synchronization of the addressed stochastic reaction–diffusion neural networks with mixed time delays via a designed impulsive controller. Compared with some recent studies, the neural network models herein are more general, some restrictions are relaxed, and the obtained conditions enhance and generalize some published ones. Finally, two numerical simulations are performed to substantiate the validity and merits of the developed theoretical analysis.

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1. Introduction

Since the pioneering work of synchronization between two chaotic systems in Pecora and Carroll (1990), the issue of synchronization has gained much research interest owing to the wide area applications in secure communication, image processing, pattern recognition, and shortest path problem (Yang & Chua, 1997). In recent years, many efforts have been dedicated to investigating synchronization of various neural network models, please refer to Guo, Yang, and Wang (2016), Liu, Zhu, and Ye (2017), Rakkiyappan, Latha, Zhu, and Yao (2017), Wan, Cao, Wen, and Yu (2016), Wu, Shi, Su, and Chu (2013) and Zhang, Ma, Huang, and Wang (2010).

Time delays do exist in neural network models because of the limited switching speeds of neuron amplifiers and the finite velocity of signal delivery, which may cause instability, bifurcation, or vibration (Sheng, Shen, & Zhu, 2017; Song, Yan, Zhao, & Liu, 2016; Zeng & Zheng, 2013; Zhang, Han, & Zeng, 2018). Actually, neural networks have spatial extensions since the existence of a large quantity of parallel pathways with plenty of axon sizes and lengths. Therefore, discrete and distributed time delays should be introduced into neural network models to exhibit the characteristics of neurons in human brains in a more realistic way (Sheng, Zhang, & Zeng, 2017b).

Diffusion phenomena cannot be ignored in physical and biological systems due to the nonuniform electromagnetic fields where electrons transport and interactions of different species, respectively. For instance, in the process of chemical reactions, different chemicals react with each other and spatially diffuse in the intermedium until a balanced-state spatially concentration pattern has been structured (Yang, Cao, & Yang, 2013). It is thus reasonable and important to consider neural networks with diffusion effects. Recently, many elegant achievements on qualitative analysis of dynamical behaviors for various reaction–diffusion neural network models have been reported in Chen, Luo, and Zheng (2016), Gan (2012), Hu, Jiang, and Teng (2010), Li and Li (2009), Liu, Zhang, and Xie (2017), Sheng and Zeng (2017a, b), Sheng, Zhang, and Zeng (2017a, c), Song, Cao, and Zhao (2006), Rakkiyappan, Dharani, and Zhu (2015), Yang et al. (2013), Zhang and Luo (2012) and Zhu and Cao (2011b), and relevant references therein.

As is known to us, stochastic perturbations frequently occur in real-world systems because of the presence of environmental noise and human disturbances (Mao, 2007; Pan & Cao, 2011; Zhu & Cao, 2011a). The research of stochastic neural networks is beneficial for us to understand how stochastic noise influences dynamical behaviors of a neural network. Currently, numerous accomplishments on dynamical analysis of stochastic neural networks have been accumulated in Bao, Park, and Cao (2016), Gan (2012), Huang,

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Li, Duan, and Starzyk (2012), Sheng and Zeng (2017b), Zhu and Cao (2011a), Zhu and Cao (2012) and Zhu, Huang, and Yang (2011).

Generally, synchronization of coupled neural networks cannot be achieved by themselves, hence, many control strategies, including feedback control (Li & Cao, 2015), adaptive control (Zhu & Cao, 2010), intermittent control (Zhang, Li, Huang, & Xiao, 2015), and impulsive control (Zhang, Ma et al., 2010), are designed for the synchronization scheme. Among them, feedback control and adaptive control are continuous time ones, which require the controller to remain active all the time. As discontinuous control techniques, the main difference between intermittent control and impulsive control is that, within a control period, the former has a nonzero control breadth, while it is a zero duration of the latter. The essence of impulsive control is to regulate the state of slave system through impulses at isolate time points such that master system and slave system can achieve synchronization. Notice that the impulsive control approach only supplies control energy at discrete impulsive moments, the control cost can therefore be reduced.

Recently, synchronization of reaction–diffusion neural networks via an impulsive controller has been extensively investigated in Chen et al. (2016), Hu et al. (2010), Liu, Zhang et al. (2017) and Yang et al. (2013). Stability and synchronization of reaction–diffusion neural networks with hybrid time delays have been discussed in Hu et al. (2010) through using the Lyapunov stability theory and inequality techniques. Different from the analysis methods in Hu et al. (2010), by utilizing Halanay's inequality, variation of parameters, and comparison principle, synchronization of coupled reaction–diffusion neural networks has been considered in Yang et al. (2013). Liu, Zhang et al. (2017) studied synchronization of reaction–diffusion neural networks and broke through the limitation that discrete time delays should be smaller than the impulsive intervals. Chen et al. (2016) constructed an impulsive-time-dependent Lyapunov functional to investigate synchronization of reaction–diffusion neural networks with hybrid time delays, additionally, the theoretical results were applied to image encryption. Meanwhile, Li and Li (2009) and Zhang and Luo (2012) considered stability of impulsive reaction–diffusion neural networks.

Note that the considered neural network models in Chen et al. (2016), Hu et al. (2010), Li and Li (2009), Liu, Zhang et al. (2017), Yang et al. (2013) and Zhang and Luo (2012) are all deterministic ones, which implies that the outcomes therein cannot be directly utilized to analyze impulsive synchronization of stochastic reaction–diffusion neural networks. To the best of the authors' knowledge, there are few published studies considering impulsive synchronization of stochastic reaction–diffusion neural networks with Dirichlet boundary conditions and hybrid time-varying delays. How to deal with reaction–diffusion neural networks, impulsive effect, stochastic noise, discrete time delay, and distributed time delay in a unified framework, and what conditions can be built to ensure impulsive synchronization of the addressed neural networks are some of the current challenges.

From the above discussion, in this study, we intend to investigate mean square exponential synchronization of stochastic reaction–diffusion neural networks with Dirichlet boundary conditions and mixed time-varying delays under a designed impulsive controller. With the help of inequality techniques, theories of stochastic analysis, linear matrix inequalities, and the contradiction method, several sufficient conditions are obtained. Compared with the neural network models in Chen et al. (2016), Hu et al. (2010), Li and Li (2009), Liu, Zhang et al. (2017), Yang et al. (2013) and Zhang and Luo (2012), distributed time delay and stochastic noise are both considered in this study.

The rest of this study is structured as follows. Preliminaries including master–slave neural network models, the definition of stochastic exponential stability, and important lemmas are given in Section 2. The main results are presented in Section 3. Two simulation examples are carried out in Section 4. Conclusions are collected in Section 5.

Notations: Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a completed probability space with the filtration $\{\mathcal{F}_t\}_{t\geq 0}$ satisfying the usual condition, that is, it is right continuous and increasing while $\mathcal{F}_0$ contains all $\mathbb{P}$-null sets. $\mathbb{E}$ is the mathematical expectation with respect to the probability measure $\mathbb{P}$. Let $\mathbb{B}(t)$ be an n-dimensional Brownian motion defined on the probability space. $\mathbb{R}^{n\times n}$, $\mathbb{R}^n$, and $\mathbb{R}_+$ correspond to the set of real matrices with order $n \times n$, n-dimensional Euclidean space, and the interval $(0, +\infty)$, respectively. If A is a vector or matrix, A^T means the transpose of A. $X = \left\{x | x = [x_1, x_2, \ldots, x_m]^T,\ |x_q| < l_q,\ q = 1, 2, \ldots, m\right\}$ is a compact set with smooth boundary ∂X and $\text{mes}X > 0$, in which $\text{mes}X$ is the measure of X, and l_q are given scalars. $B = \text{diag}\{b_1, b_2, \ldots, b_n\}$ means that B is a diagonal matrix. If C is a square matrix, $C > 0$ implies that C is a positive definite symmetric matrix. As to a symmetric matrix, symmetric terms are marked by $*$ which can be deduced from symmetry. I denotes the identity matrix. $\mathbf{0}_{n\times 1} \in \mathbb{R}^n$ represents the zero vector. Let $z(x, t) = [z_1(x, t), z_2(x, t), \ldots, z_n(x, t)]^T$, 2-norm of $z(x, t)$ is defined as $\|z(x, t)\|_2 = \left\{\int_X \sum_{i=1}^n z_i^2(x, t)dx\right\}^{(1/2)}$. Vectors and matrices, if their dimensions are not distinctly expressed, are assumed to have appropriate dimensions.

2. Preliminaries

Consider reaction–diffusion neural networks with hybrid time-varying delays described by

$$du(x, t) = \left\{ \sum_{q=1}^{m} \frac{\partial}{\partial x_q} \left[D_q \frac{\partial u(x, t)}{\partial x_q} \right] - Au(x, t) \right. + B\hat{f}(u(x, t)) + C\hat{g}(u(x, t - d(t))) \left. + E \int_{t-\tau(t)}^{t} \hat{h}(u(x, s))ds + \mathbb{I} \right\} dt \tag{1}$$

where $u(x, t) = [u_1(x, t), u_2(x, t), \ldots, u_n(x, t)]^T$ is the state vector of n neurons in space x and at time t, $D_q = \text{diag}\left\{D_{1q}, D_{2q}, \ldots, D_{nq}\right\} \geq 0$ represents the transmission diffusion coefficient, $\sum_{q=1}^m \frac{\partial}{\partial x_q} \left[D_q \frac{\partial u(x,t)}{\partial x_q}\right]$ denotes the reaction–diffusion term, $A = \text{diag}\{a_1, a_2, \ldots, a_n\} > 0$ is the self-feedback coefficient matrix, $B = [b_{ij}]_{n\times n}$, $C = [c_{ij}]_{n\times n}$, and $E = [e_{ij}]_{n\times n}$ are connection weight matrix, discretely delayed connection weight matrix, and distributively delayed connection weight matrix, respectively, $d(t)$ and $\tau(t)$ correspond to discrete and distributed time-varying delays, respectively, $\hat{f}(u(x, t)) = \left[\hat{f}_1(u_1(x, t)), \hat{f}_2(u_2(x, t)), \ldots, \hat{f}_n(u_n(x, t))\right]^T$, $\hat{g}(u(x, t - d(t))) = \left[\hat{g}_1(u_1(x, t - d_1(t))), \hat{g}_2(u_2(x, t - d_2(t))), \ldots, \hat{g}_n(u_n(x, t - d_n(t)))\right]^T$, and $\hat{h}(u(x, s)) = \left[\hat{h}_1(u_1(x, s)), \hat{h}_2(u_2(x, s)), \ldots, \hat{h}_n(u_n(x, s))\right]^T$ are activation functions, and $\mathbb{I}$ is an external input.

Associated with neural networks (1), initial and boundary value conditions are as follows:

$$u(x, s) = \Phi(x, s), \quad x \times s \in X \times [-\hat{d}, 0] \tag{2}$$

$$u(x, t) = \mathbf{0}_{n\times 1}, \quad x \times t \in \partial X \times [-\hat{d}, +\infty) \tag{3}$$

in which $\Phi(x, s) \in \mathbb{R}^n$ is bounded and continuous, and $\hat{d} = \max\{d, \tau\}$ (d and τ are upper bounds of $d(t)$ and $\tau(t)$ in neural networks (1), respectively, please refer to Assumption 1 for details).

Before moving on, some assumptions are given.

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