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Anti-synchronization transmission of the laser signal using uncertain neural network

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ABSTRACT

Anti-synchronization transmission of the laser signal using uncertain neural network is investigated in this paper. Based on sliding mode control theory, the suitable sliding mode surface and the appropriate sliding mode control input are both designed to guarantee anti-synchronization, and the uncertain coefficient in the network can be effectively identified using the adaptive law of the uncertain coefficient. Finally, a numerical example is given to illustrate the effectiveness of the proposed synchronization technique.

1. Introduction

Neural network is a system with powerful and efficient information processing capability and one of its outstanding features is a large-scale node connected to each other. Though these nodes maybe simple, their collections are complex and information processing can be parallel and distributed. In addition, the neural network also exhibits strong robustness. The weak damage in small amount of nodes will not destroy the overall performance of the network. Thus far, neural network has been applied comprehensively in many fields, such as pattern recognition, nonlinear analysis and identification, troubleshooting, signal transmission, computer, and so on, because of its unique advantages and a great deal of important progress of the relevant theories about the investigation of neural network has also been achieved [1–6].

In recent years, it is found that, whether neural network or small-world network, scale-free network and regular network existed in the real world, they take on a very interesting and significant collective behavior, that is, it is a synchronization phenomenon of complex network. It is well known that many phenomena in real world have close relation with synchronization of complex networks, for example, the synchronous transmission of information on World Wide Web, Internet and the cooperation of lasers, etc. Apparently, the synchronization of neuronal network is also very important for the efficient processing and transmission of information.

The groundbreaking work of the systematic investigation about complex network synchronization is marked by Pecora and Carroll [7]. In their work, the definition of network synchronization is given firstly, the variational equation of network synchronization status is further obtained by utilizing linear stability analysis and the condition of network synchronization is gained finally using the master stability function criterion. After this, Belykh et al. proposed a connection diagram method to discuss network synchronization [8], which combines the Lyapunov function approach with graph theoretical reasoning. In particular, contrary to the master stability function approach developed by Pecora and Carroll, the connection graph stability method leads to global stability of synchronization and it permits not only constant, but also time-dependent interaction coefficients. In addition, the Lyapunov stability method is also a typical method of network synchronization. Depending on different control inputs, the method can be divided into adaptive control, impulse control, and pinning control, and so on [9–13].

The research objects for network synchronization were initially simple regular networks. With the deepening of research, they have been extended to small-world network, scale-free network and neural network. In recent years, the typical works of neural network synchronization have been reported. For examples, Rossoni et al. studied the synchronization dynamics for the system of two Hodgkin-Huxley (HH) neurons coupled diffusively or through pulselike interactions [14]; Guo et al. discussed the synchronous behavior of interneuronal networks coupled by delayed inhibitory and fast electrical synapses [15]; Baptista et al.

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analyzed the combined action of chemical and electrical synapses in small networks of Hindmarsh-Rose (HR) neurons on the synchronous behavior and the rate of information produced by the networks [16]; Yu et al. researched the dependence of synchronization transitions in small-world networks of bursting neurons with hybrid electrical-chemical synapses on the information transmission delay, the probability of electrical synapses and the rewiring probability [17]; Wu and Park investigated master-slave synchronization which has been used for discrete-time time-delay neural networks [18].

In the literatures reported about the synchronization of neural network, the parameters of network node are certain. In practice, however, the parameters of network node are always unstable or cannot be determined accurately in advance because of external interference or limitation of technology. Therefore, the investigation of synchronization for uncertain neural network is of more practicability. In this paper, we mainly consider the anti-synchronization problem of a class of uncertain neural network based on sliding mode control (SMC) method. The uncertain coefficients of the neural network is estimated using an adaptive technique and sliding mode input is then proposed to ensure the existence of the sliding motion. Finally, the effectiveness and robustness of the proposed synchronization technique is numerically verified.

2. Anti-synchronization mechanism of neural network

Consider the time-delay neural network described by [19]

$$\dot{x}_i(t) = -c_i x_i(t) + \sum_{j=1}^{n} a_{ij} f_j\left(x_j(t)\right) + \sum_{j=1}^{n} b_{ij} f_j\left(x_j((-\tau)\right) + u_i \tag{1}$$

where, n is the number of neurons in the network, $x_i(t)$ denotes the state variable associated with the ith neuron, c_i is a coefficient and assume it is uncertain. $f_j\left(x_j(t)\right) = (\left|x_j(t)+1\right| - \left|x_j(t)-1\right|)/2$ is the activation function and it describes the manner in which the neurons respond to each other. $A = \left(a_{ij}\right)_{n\times n}$ is feedback matrix which determines the weights of the neuron interconnections within the network. Nevertheless, the delayed feedback matrix $B = \left(b_{ij}\right)_{n\times n}$ determines the weights of the neuron interconnections within the network with time delay. τ is the delay parameter.

Assume that the synchronization target is the laser signal, it can be described by

$$\dot{x}_d(t) = G(x_d(t)) \tag{2}$$

Define the error between the network and the synchronization target

$$e_i(t) = x_i(t) + x_d(t) \quad (i = 1, 2, \cdots, n) \tag{3}$$

It is easy to find the dynamics of the error as follows

$$\begin{aligned}\dot{e}_i(t) = & -c_i x_i(t) + \sum_{j=1}^{n} a_{ij} f_j\left(x_j(t)\right) + \sum_{j=1}^{n} b_{ij} f_j\left(x_j(t-\tau)\right) + u_i \\ & + G(x_d(t))\end{aligned} \tag{4}$$

To propose an anti-synchronization mechanism of neural network, the sliding surfaces are considered as

$$s_i = (\frac{d}{dt} + \lambda_i)\varphi_i(t) \tag{5}$$

where, $\varphi_i(t)$ is an function given by

$$\varphi_i(t) = \int_0^t e_i(\theta)d\theta \tag{6}$$

and λ_i is an arbitrary positive coefficient.

According to the sliding mode control theory, it must satisfy $s_i = \dot{s}_i = 0$ when the sliding mode surface is moving. Then, it can be obtained

$$\dot{e}_i(t) = -\lambda_i e_i(t) \tag{7}$$

It is easy to know that $\lambda_i > 0$, the sliding mode surface designed is asymptotically stable.

In order to determine the adaptive law of the uncertain coefficient and the sliding mode control input in the neural network, the Lyapunov function is constructed as

$$V = \frac{1}{2}\sum_{i=1}^{n} s_i^2 + \frac{1}{2}\sum_{i=1}^{n} \xi_i(\hat{c}_i - c_i)^2 \tag{8}$$

where, $\hat{c}_i$ stands for the identification of the uncertain coefficient in the neural network and ξ_i is an adjustment parameter.

Differentiating Eq. (8) with respect to time is defined as

$$\begin{aligned}\dot{V} &= \sum_{i=1}^{n} s_i \dot{s}_i + \sum_{i=1}^{n} \xi_i(\hat{c}_i - c_i)\dot{\hat{c}}_i \\ &= \sum_{i=1}^{n} s_i \left[-c_i x_i(t) + \sum_{j=1}^{n} a_{ij} f_j(x_j(t)) + \sum_{j=1}^{n} b_{ij} f_j(x_j(t-\tau)) + u_i + G(x_d(t)) + \lambda_i e_i(t) \right] \\ &+ \sum_{i=1}^{n} \xi_i(\hat{c}_i - c_i)\dot{\hat{c}}_i\end{aligned} \tag{9}$$

The adaptive law of the uncertain coefficient c_i and the sliding mode control input u_i of the network are designed as

$$\dot{\hat{c}}_i = -\frac{1}{\xi_i} s_i x_i(t) \tag{10}$$

$$\begin{aligned}u_i = & \hat{c}_i x_i(t) - \sum_{j=1}^{n} a_{ij} f_j(x_j(t)) - \sum_{j=1}^{n} b_{ij} f_j(x_j(t-\tau) - G(x_d(t)) - \lambda_i e_i(t) \\ & - \eta_i s_i\end{aligned} \tag{11}$$

where, η_i is a positive adjustment parameter.

Using Eqs. (10) and (11), let us rewrite Eq. (9) as

$$\begin{aligned}\dot{V} &= \sum_{i=1}^{n} s_i \left[-c_i x_i(t) + \sum_{j=1}^{n} a_{ij} f_j(x_j(t)) + \sum_{j=1}^{n} b_{ij} f_j(x_j(t-\tau)) + u_i + G(x_d(t)) + \lambda_i e_i(t) \right] \\ &+ \sum_{i=1}^{n} \xi_i(\hat{c}_i - c_i)\dot{\hat{c}}_i \\ &= \sum_{i=1}^{n} s_i[(\hat{c}_i - c_i)x_i(t) - \eta_i s_i] + \sum_{i=1}^{n} \xi_i(\hat{c}_i - c_i)\dot{\hat{c}}_i \\ &= -\sum_{i=1}^{n} \eta_i s_i^2\end{aligned} \tag{12}$$

Therefore, the condition $\dot{V} < 0$ will be satisfied. According to Lapunov theorem, the anti-synchronization of uncertain neural network is realized.

3. Numerical example

In this section, an illustrative example is provided to show the effectiveness of our results.