Neurocomputing 189 (2016) 72–79

Contents lists available at ScienceDirect

Neurocomputing

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

Brief Papers

Optimization of hysteretic chaotic neural network based on fuzzy sliding mode control

Guowei Xu, Fengnan Liu, Chunbo Xiu, Liankun Sun *, Chang Liu

Key Laboratory of Advanced Electrical Engineering and Energy Technology, School of Electrical Engineering and Automation, Tianjin polytechnic University, Tianjin 300387, China

ARTICLE INFO

Article history:
Received 20 October 2015
Received in revised form
11 December 2015
Accepted 18 December 2015
Communicated by: Hongyi Li
Available online 8 January 2016

Keywords:
Hysteretic chaotic neural network
Chaos
neuron
Sliding mode control
Fuzzy

ABSTRACT

A hysteretic chaotic neural network with the uncertain term is constructed, and a novel control strategy based on fuzzy sliding mode is proposed to control its dynamic behaviors without changing its structure. The control law contains fuzzy inference term which can reduce the chattering on the sliding mode. The system stability is proved by the Lyapunov theory. The hysteretic chaotic neural network based on the fuzzy sliding mode control can be used to resolve the function optimization problem without destroying chaos generation mechanism and changing the structures of the neural network, which is different to the common annealing optimization strategy. Simulation results prove that the control strategy is a valid method to control the dynamic behaviors of the neural network and resolve the function optimization problem.

1. Introduction

Earlier artificial neural network, mimicking natural biological neural system, has simple structure by ignoring some nonlinear characteristics, such as chaos, hysteretic, etc. However, these nonlinear characteristics actually play important roles in the information processing for the neural system. Such as, hysteretic characteristic can help to enhance the capacity of memory and steadiness of the original states for the neural network, and chaotic characteristic can reflect some perception phenomenon or cognitive process of human. Therefore, many neural networks with kinds of nonlinear characteristics are proposed to improve the performance of the conventional neural network [1–3]. Accordingly, many control strategies are used to control these nonlinear characteristics in the neural network to play their roles in intelligent information processing [4–6]. Especially, the study on chaotic neural network attracts much attention of investigators, and many chaotic neural network models are proposed to resolve practical engineering problems [7,8]. Generally, chaotic neural network models fall into two categories. First, chaotic neural networks are coupled by some chaotic oscillators or neurons, such as Hindmarsh–Rose neural system [9], GCM [10], S-GCM [11,12], SI-GCM [13], etc. Second, chaotic behaviors can be shown in some dynamic neural networks by adding special connected weights, such as Hopfield neural network [14], cellular neural network [15], bidirectional associative memory network [16], recurrent multilayer perceptions [17], etc. Likewise, hysteretic chaotic neural network [18,19] is based on Hopfield neural network. Its chaotic characteristic is generated by adding self-feedback weights in Hopfield neural network, and its hysteretic characteristic is generated by changing the activation function as the hysteretic activation function in Hopfield neural network. It can simultaneously show two non-linear characteristics: chaos and hysteresis. Thus, the neural network has the more complex dynamic behaviors and flexibly structure. Therefore, it has good potential application for information process.

Because chaotic neural network has complex dynamic characteristics, the study on chaos control or chaos synchronization is the basis for utilizing chaotic neural network to resolve the practical engineering problems [20–22]. Chaos in the complex system can be controlled by many nonlinear control methods [23–25]. For now, Synchronization of chaotic neurons or chaotic neural networks has been intensively studied. Many synchronization strategies have been proposed to synchronize two identical or different chaotic neural networks, such as impulsive control scheme [26–28], time delay feedback control [29], adaptive control [30,31], periodically intermittent control [32], fuzzy control [33–35], etc. In contrast, chaos control of chaotic neuron or chaotic neural networks is performed generally by changing the control parameters or structure of neurons or neural networks. Such as, a sinusoidal wave is used to modulate the control parameter of chaotic neural network to perform associative memory in Ref. [36], chaos is controlled in a self-adaptive manner by perturbing the decay parameter and refractory scaling parameter of the system with a

* Corresponding author.
E-mail address: slk300@126.com (L. Sun).

http://dx.doi.org/10.1016/j.neucom.2015.12.055
0925-2312/

dynamic depression control signal in Ref. [37], SI-GCM chaotic neural network is controlled to specified-period orbit by adopting a variable threshold parameter control method in ref [13], and chaotic neural network is controlled by limiting a time-varying threshold in Ref. [38]. Furthermore, annealing controlling is also a common method to control chaotic neural network [39]. Thus it can be seen that chaos in the neuron or neural network is commonly controlled by destroying its generation mechanism or changing the structures of the networks to make the neural network lose the chaotic characteristic. In other words, chaos in the neuron or neural network is not controlled by the control theory, and the controllability of chaos in the neuron or neural network is not deeply explored. Likewise, hysteretic chaotic neural network [18,19] can be used to resolve associative memory and function optimization problems by annealing strategy. After decaying the hysteretic parameters and self-feedback weights, hysteretic chaotic neural network becomes the conventional Hopfield neural network.

More remarkable, most of chaotic neural networks are deterministic. However, considering the inevitable temperature-drift and creep of the parameters in the actual system, some uncertainty must exist in the neuron and neural network. Therefore, it is more practical to construct and apply the neural network with the uncertainty [40–43].

Different to the conventional model, the uncertainty is considered in the process of constructing the hysteretic chaotic neuron and network in this paper. That is, The hysteretic chaotic neuron and hysteretic chaotic neural network with uncertain disturbance is constructed. The controllability of chaos in the hysteretic chaotic neuron and neural network is deeply explored, and the control strategy based on fuzzy sliding mode is proposed to control the states of neuron and neural network to get to the desired states. It is also possible to extend the control results for the general nonlinear systems based on fuzzy dynamic models [44,45] and the underlying systems under the network-based environment with time-delays, packet dropouts or quantization [46].

Generally, the function optimization problem can be resolved by the deterministic neural network. In this paper, the uncertain neuron and neural network are innovatively used to resolve the function optimization problem by the fuzzy sliding mode control. That is, the control strategy can control the state of neuron or neural network to converge to the optimal point of the function optimized.

In Section 2, the mathematical models of the hysteretic chaotic neuron and the hysteretic chaotic neural network are given, and the chaotic behaviors of hysteretic chaotic neuron and hysteretic chaotic neural network are investigated. In Section 3, a fuzzy sliding mode control strategy is proposed to control the sate of hysteretic chaotic neuron and neural network with the uncertain disturbance to the desired state. In Section 4, the fuzzy sliding mode control strategy is used to resolve the function optimization problem. In Section 5, simulation results are given to prove the validity of the fuzzy sliding mode control strategy. A brief conclusion is given in Section 6.

The notations are standard. The notation r represents reference input, and e represents the control error. V denotes a Lyapunov function, and E denotes an energy function. $f(\ )$ and sgn ( ) represent, respectively, the activation function and the sign function.

2. Hysteretic chaotic neuron and hysteretic chaotic neural network

The mathematical model of hysteretic chaotic neuron [18,19] is described as follows:

$$\begin{aligned} y(t+1) &= ky(t) - \alpha[x(t) - I] \\ x(t) &= f[y(t)] \end{aligned} \tag{1}$$

$$f(s) = \begin{cases} (1+\exp[-c(s+a)])^{-1}, \dot{s}(t-\delta t) > 0 \\ (1+\exp[-c(s-b)])^{-1}, \dot{s}(t-\delta t) < 0 \end{cases}$$

$$\dot{s}(t-\delta t) = \lim_{\delta t \to 0} [s(t) - s(t-\delta t)]/\delta t$$

where, $x(t)$ and $y(t)$ are the output of neuron and the inner state of neuron at discrete time t, I is the input bias of neuron, the activation function $f()$ with the parameters a, b and c has two response branches which form a hysteretic loop in the interval $(-\infty, +\infty)$. α is the self-feedback gain coefficient.

The hysteretic chaotic neuron is constructed by adding the self-feedback gain α into the conventional neuron and changing the common Sigmoid activation function as the hysteretic activation function. In this way, hysteretic characteristic and chaotic characteristic are brought into neuron simultaneously. The bifurcation diagram and the Lyapunov exponent diagram of the neuron with the parameters $k=1.0$, $a=b=0.8$, $I=0.86$, $c=250$ are shown in Fig. 1.

Set $\alpha=0.098$ and change the hysteretic parameters $a=b$, the Lyapunov exponent diagrams can be shown in Fig. 2.

According to the Fig. 2 above, the chaotic degree of the neuron is sensitive to the hysteretic parameters a and b which increase the complexity of the dynamic behaviors of the neuron.

Hysteretic chaotic neural network based on the hysteretic chaotic neuron above can be constructed as follows:

$$\begin{aligned} x_i(t) &= f[y_i(t)] \\ y_i(t+1) &= ky_i(t) + \beta\left[\sum_{j=1, j\neq i}^{n} w_{ij}x_j(t) + I_i\right] - \alpha[x_i(t) - I_0] \end{aligned} \tag{2}$$

where the parameter β is the coupling coefficient among the neurons, and w_{ij} is the weight between neuron i and neuron j. The

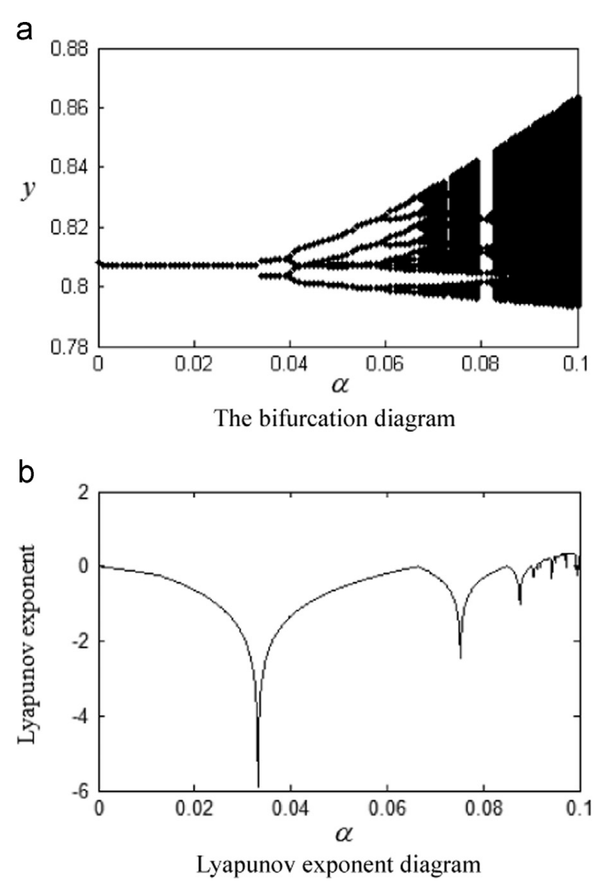

Fig. 1. The bifurcation diagram and Lyapunov exponent diagram of neuron. (a) The bifurcation diagram and (b) Lyapunov exponent diagram.