Pattern Recognition in Chaotic Neural Networks

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Abstract

A chaotic neural networks (CNNs) constructed with chaotic neurons have rich dynamics. The CNNs can generate chaotic associative memory dynamics and has been denoted to be a promising technique in information processing, such as pattern recognition or memory search. But the outputs of the CNNs wander around all stored patterns and can not be stabilized in one of its stored patterns or a periodic orbit. It is difficult to judge when to terminate the chaotic dynamics, which is imperative in information processing. In this paper, we discuss pattern recognition in a CNNs. We propose a chaos control method firstly for the CNNs. Then we employ the controlled CNNs to carry out pattern recognition tasks. The simulation results show that the outputs of the controlled CNNs are period, not a fixed point. The outputs are dependent on initial pattern. The controlled network has the ability of identifying two initial patterns with small difference. This is an advantage of CNNs comparing with Hopfield model.

Keywords: Chaotic neural networks; Controlled dynamics; Pattern recognition; Controlling chaos

1 Introduction

Pattern recognition is one of important fields of artificial intelligence. One focuses on how a system can observe the environment, distinguish patterns of interest from their background and make decisions about their classification or categorization in pattern recognition study. Many methods and techniques have been proposed for pattern recognition, for example, the template matching, syntactic or structural matching, statistical classification, and artificial neural networks (ANNs) approaches[1]. ANNs have the ability of learning complex nonlinear input-output relationships and therefore drawn more and more attentions in recent years. However, there is an essential difference between ANNs approaches and the brain in pattern recognition. Once an output pattern is identified, ANNs remains in the state until the arrival of next external input, but the brain does not "stick" to the state and can recall other associative memory patterns without additional external stimulus when a pattern is retrieved from a memory location. A conventional artificial neuron model is a simply threshold element transforming a weighted summation of inputs into the output through a nonlinear output function with threshold. This model is oversimplified so that the actual characteristics of the biological neurons that have the ability to "jump" from one memory state to another in the absence of a stimulus cannot be represented in such neuron model. Biological neurons have chaotic behaviors which was observed in a single neuron by electrophysiological experiments[2], but chaotic behaviors are lack in the conventional artificial neurons. Therefore various neuron models and neural networks with chaotic dynamics have been proposed and investigated[3-6]. In this paper, we focus on a chaotic neural networks (CNNs)[3] composed of chaotic neurons which were proposed based on electrophysiological experiments in the squid giant axons. The chaotic neuron model and CNNs have been shown to have rich dynamics. Adachi et al.[7] have proved that the CNNs can generate chaotic associative memory dynamics in several parameter regions. Due to the chaotic associative memory dynamics, the CNNs is expected to be use in information processing, such as pattern recognition or memory search, etc. However, the outputs of the CNNs wander around all stored patterns and can not be stabilized in one of its stored patterns or a periodic orbit. It is difficult to judge when to terminate the chaotic dynamics, which is imperative in pattern recognition. The chaos control techniques for the CNNs were therefore proposed by Nakamura *et al*.[8], Kushibe *et al*. [9], He *et al*.[10] etc. In Ref. 8 and 9, the chaos in the CNNs was controlled by making the CNNs to a Hopfield model[11]. The output of the controlled networks is a fixed point. The pattern recognition or memory search therefore achieved. However, the control target is refereed by comparing the initial pattern with stored patterns in their works. In other words, the initial pattern mapped on a stored pattern had been assigned *a priori*, which limits the real application in pattern recognition. Besides, a fixed output of the controlled CNNs makes the CNNs lost advantages of chaotic dynamics. In Ref. 10, the control target also should been assigned. Tan and Ali[12] proposed a synchronization method to achieve pattern recognition in a neural network with chaos. However, the desired orbit also should been assigned *a priori* too.

In order to promote the CNNs to be used in information processing, such as pattern recognition, memory search, a chaos control method without assigning a control target, i.e. a self-adaptive chaos control method, is necessary. In this paper, we will propose a chaos control method which need not assign control target or desired orbit for the CNNs. Then we will perform pattern recognition task by using the controlled CNNs.

The article is organized as follows. In section 2, the models of the CNNs are described briefly. A chaos control method for CNNs is proposed. In section 3, we apply the controlled CNNs to carry out the pattern recognition task. The discussion and conclusion are given in the final section.

2 Chaotic Neural Networks and Chaos Control Method

2.1 Chaotic Neural Networks model

A chaotic neural networks (CNNs) used for pattern recognition is constructed with chaotic neurons by considering the spatio-temporal summation of both external inputs and feedback inputs from other chaotic neurons[3]. The structure of the CNNs is shown in figure 1. When the external input term is temporally constant, it can be included in the threshold term. The dynamics of the *i*th chaotic neuron in the CNNs at time *t* can be described simply as follows:

$$x_i(t+1) = f\big(\eta_i(t+1) + \zeta_i(t+1)\big), \tag{1}$$

$$\eta_i(t+1) = k_f \eta_i(t) + \sum_{j=1}^{N} w_{ij} x_j(t), \tag{2}$$

$$\zeta_i(t+1) = k_r \zeta_i(t) - \alpha x_i(t) + a_i, \tag{3}$$

$$f(x) = \frac{1}{1+\exp(-x/\varepsilon)}. \tag{4}$$

where the $x_i(t)$ is the output of the *i*th chaotic neuron at time step *t*, the $\eta_i(t)$ and $\zeta_i(t)$ are the internal state variables of feedback input from the constituent neurons in the network and refractoriness of the chaotic neuron at time *t*, respectively. N is the number of neurons in the network. k_f and k_r are the decay parameters of the feedback inputs and the refractoriness, respectively. The parameter a_i is the threshold of the *i*th neuron. The parameter α is the refractory scaling parameter of a neuron, and the output function of neuron $f(\cdot)$ is sigmoidal function with the steepness parameter ε described by equation (4). w_{ij} are synaptic weights to the *i*th constituent neuron from the *j*th constituent neuron. A neuron does not receive the synaptic connection from itself, i.e. w_{ii} =0. The weights are defined according to the following symmetric auto-associative matrix of n binary patterns:

$$w_{ij} = \frac{1}{n}\sum_{p=1}^{n}(2x_i^p - 1)(2x_j^p - 1), \tag{5}$$

where x_i^p is the *i*th component of the *p*th binary pattern with a discrete value of 0 or 1. In this way, the binary patterns can be stored as basal memory patterns in the network. n is the total number of stored memory patterns.

In the paper, four patterns shown in Fig. 2 are employed as stored memory patterns, or namely learning patterns. Each pattern is composed of 10 by 10 binary pixels. Correspondently the network is constructed with 100 neurons, that is N = 100. A neuron will be represented by a block "■" when its output, x_i, is equal to 1, which means the neuron is "excited", while a neuron is denoted by a dot "·" when its output is equal to 0, which means the neuron is "resting".

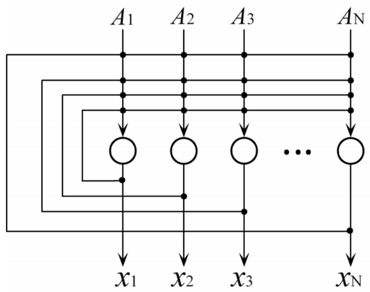

Figure 1 The structure of the CNNs

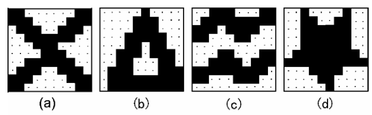

Figure 2 Four stored patterns

The dynamics of the chaotic neural networks is dependent on the network parameters. In our numerical simulations the network parameters are kept as follows: k_r=0.95, k_f=0.20, α = 10.0, a_i=2.0 (i=1, 2, …, 100), and ε = 0.015. It has been shown that the CNNs with above parameters is chaotic[7, 10]. The outputs of the CNNs are wandering around all stored and their reversal patterns, namely associative memory dynamics [7].

2.2 Chaos control method

The chaos control technique was proposed firstly by Ott et al. in 1990(OGY method)[13]. Since the pioneer work of OGY, the chaos control methods have been greatly developed. Although most of these controlling methods have been mainly applied to chaotic system with small degree of freedoms, several methods have been adopted for a system with large degree of freedoms, such as CNNs [8-10]. Nakamura *et al.*[8], Kushibe *et al.*[9], He et al.[10], had proposed chaos control methods for the CNNs, but in their methods, the control target should been assigned. Their control methods can not been applied to real information processing. In order to make the CNNs to be used in pattern recognition with chaotic dynamics, we purpose a new scheme of controlling chaos for the CNNs by considering following aims: (I) the output of the controlled CNNs can be stabilized to a periodic orbit or a fixed point; (II) the stable output of the controlled CNNs should be related with the stored patterns and initial state of the network. (III) the control target should not been assigned, i.e. the control method is a self-adaptive method. In our previous work[14], we have known that the chaotic dynamics in the CNNs is dependent on the refractory scaling parameter of the neurons. When the refractory scaling parameter is small, the dynamics of the CNNs is a fixed points or periodic. As the refractory scaling parameter increase, the output of the CNNs becomes chaotic. We therefore assume the chaos in CNNs can be controlled if the refractory scaling parameter of the neurons is changed by a control signal. This is the idea of our control method to be proposed here. Considering self-adaptive method, we take the delay feedback signal as the control signal. The controlled CNNs is described in following equations:

$$x_i(t+1) = f(\eta_i(t+1) + \zeta_i(t+1)), \tag{6}$$

$$\eta_i(t+1) = k_f \eta_i(t) + \sum_{j=1}^{N} w_{ij} x_j(t), \tag{7}$$

$$\zeta_i(t+1) = k_r \zeta_i(t) - \alpha \beta^{k_c u(t)} x_i(t) + a_i, \tag{8}$$

$$u(t) = \sum_{i}^{N} |x_i(t) - x_i(t-\tau)|. \tag{9}$$

where $u(t)$ is a control signal determined by the difference of the output of the chaotic neuron at different time, β is a control parameter, a positive value smaller than 1.0, k_c is a control strength. When the output of the chaotic neuron is chaos, the control signal $u(t)$ is not zero and $\alpha\beta^{k_c u(t)} < \alpha$. Thus the dynamics of the chaotic neuron will be changed.

3 Pattern Recognition

Now we investigate the pattern recognition in CNNs. After the CNNs learning the stored pattern shown in figure 2, the output sequence of the CNNs wanders around all stored pattern and their reversal patterns, as mentioned in introduction, namely associative memory dynamics[7]. We perform chaos control in CNNs according to proposed control method by equations (6) ~ (9). The parameters of the control method are taken as β = 0.945, τ = 3 and k_c = 0.6. As pattern recognition tasks, we take stored patterns shown in figure 2 and noisy stored patterns, patterns with small noises to stored patterns, as the initial patterns, and investigate output sequences of the controlled CNNs. A initial pattern is injected in the CNNs by taking $x_i(0)$ as the initial pattern in the internal state η_i and ζ_i. The initial internal states are set as 0. We find the dynamics of the network is changed when the CNNs is controlled by equations(6) ~ (9). The output sequences of the controlled chaotic neural networks are periodic. The period and the output sequence are dependent on the initial states. Due to the limited space, we only show the periodic output sequence slice of the controlled CNNs in figure 3. The left parts of the figure are the initial patterns, the right parts are the output sequence of one period of the controlled network.

From the figure, one can find no matter a initial pattern is a stored pattern (top four initial patterns) or its noisy pattern (bottom four initial patterns), the most part of patterns appearing in the output periodic sequence of the controlled CNNs are the stored pattern and its reversal pattern while other stored patterns and their reversal patterns are not appeared in the output sequence. That is, the controlled CNNs can identify the initial pattern from the stored patterns. The pattern recognition tasks are therefore achieved.

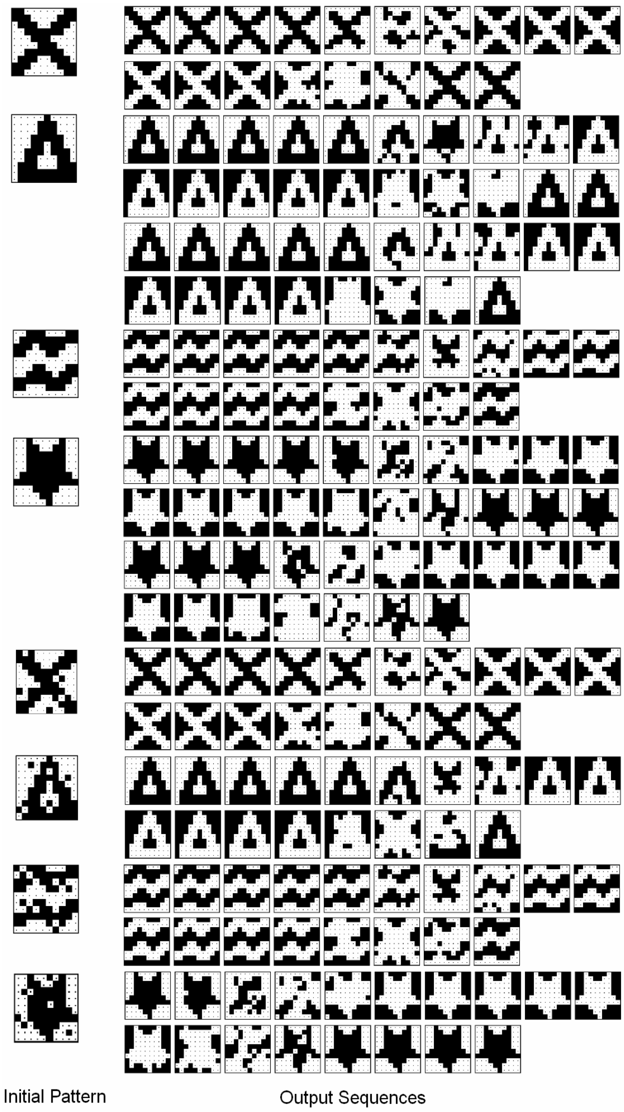

Figure 3 Initial patterns and their response output sequence slice of the controlled CNNs. The left parts of the figure are the initial patterns, the right parts are the output sequence of one period of the controlled network. The control parameters are taken as β = 0.945, τ = 3 and k_c = 0.6.

4 Discussion and Conclusion

To promote the CNNs to be a technique of information processing, such as pattern recognition, memory search, a self-adaptive chaos control method for the CNNs was proposed based on the fact that the dynamics of the chaotic neural networks is dependent on the refractory scaling parameter. The controlled CNNs was employed to carry out pattern recognition tasks. The simulation results have shown that the chaotic dynamics disappear when the refractory scaling parameter is changed by a control signal which is determined by the difference of two outputs with time delay. The dynamics of the controlled CNNs is periodic. The output sequences of the controlled CNNs are dependent on the initial pattern. The pattern recognition tasks are therefore achieved.

We control the CNNs to be a periodic state, not a fixed point as in Ref. 8 and 9, which make the output sequences of the controlled CNNs sensitive to the initial state. From figure 3, we find the period and the output pattern sequences of the controlled CNNs are different when the initial pattern are a stored pattern (b) shown in Fig. 2 and its noisy stored pattern. The same situation exists when the initial patterns are a stored pattern (d) and its noisy stored pattern, which means the controlled CNNs is sensitive to the initial state. In fact, when control parameter β take as 0.95, the output sequences of the controlled CNNs with a stored pattern taken as an initial pattern are different from those with its noise pattern as the initial pattern even if the period is same. We do not show the results of $\beta = 0.95$ here because the period of the controlled CNNs is long and it is difficult to show the output sequences in a short space. The sensitiveness to the initial state in our controlled method means the controlled CNNs can distinguish initial patterns with small difference. This is the advantage of our controlled CNNs compared to previous control methods [8, 9], or the conventional auto-associative network, such as Hopfield network[11], where the output converge on a fixed point, no matter the initial pattern is a stored pattern or a noisy stored pattern.

It should be notice that a rejection mechanism is lack in the controlled CNNs. It means that an initial pattern may be attracted to a stored pattern though it shows low similarity with the stored pattern. Proposing an improved control method or an improved CNNs model, with which the CNNs not only recognize an initial pattern if it has high similarity with a stored pattern but also reject recognizing as any stored pattern if it has low similarity with a stored pattern, will be our future direction.

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