PAPER

A Type of Delay Feedback Control of Chaotic Dynamics in a Chaotic Neural Network

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SUMMARY A chaotic neural network consisting of chaotic neurons exhibits such rich dynamical behaviors as nonperiodic associative memory. But it is difficult to distinguish the stored patterns from others, since the chaotic neural network shows chaotic wandering around the stored patterns. In order to apply the nonperiodic associative memory to information search or pattern identification, it is necessary to control chaotic dynamics. In this paper, we propose a delay feedback control method for the chaotic neural network. Computer simulation shows that, by means of the control method, the chaotic dynamics in the chaotic neural network are changed. The output sequence of the controlled network wanders around one stored pattern and its reverse pattern.
key words: *controlling chaos, delay feedback control, chaotic dynamics, chaotic neural network*

1. Introduction

In the last decade, the chaotic neural network has received much attention because chaotic dynamics exist in real neurons and neural network [1]–[4]. From the view point of different network models and strategies, network dynamics have been investigated in order to show functional roles in the information processing of a biological system [5]–[15]. In this paper, we focus on a chaotic neural network model consisting of chaotic neurons proposed by Aihara et al. [16] as based on biological experiments in squid giant axons [1], [2]. Kuroiwa et al. [17] have investigated the dynamical properties of a single chaotic neuron in stochastic inputs. Adachi and Aihara [18] have proved that a chaotic neural network model can generate chaotic associative memory dynamics in several parameter regions.

It is well known that chaotic neural network shows rich dynamics with various coexisting attractors, not only of fixed points and periodic orbits but also of strange attractors. Although it has been shown that the chaotic dynamics can be promising techniques for information processing, the outputs of the chaotic neural network wander around all stored patterns which change continuously and cannot be stabilized in one of its stored patterns, that is, the convergence problems have not yet been satisfactorily solved in relation to chaotic dynamics. One, therefore, meets difficulties in the application of chaotic dynamics in information processing. To achieve such information processing as memory search or pattern identification in chaotic neural network, it is necessary to control chaos in chaotic neural network. In our previous work, we proposed a pinning control method [19]. By means of this control method, the chaotic neural network can be stabilized in one stored pattern. However, in the pinning control method, the portion of the target pattern has to be assigned *a priori*. Thus, in the case that the target pattern or its portion is known before calculation is started, the pinning control method is practical. In this paper, we focus on the control method in which the target pattern or its portion is not necessarily known *a priori*. One of such methods is the "delay feedback control (DFC) method" [20]. The purposes of this paper are: (i) To propose a delay feedback control method available for a chaotic neural network model; (ii) To investigate the dynamics of an orbit controlled by our DFC method; (iii) To investigate control parameters which determine the dynamics in the controlled neural network.

In the next section, we give a brief description of the chaotic neural network employed in this paper. In the third section, the delay feedback control in the chaotic neural network is proposed. The results of the computer simulation will be shown in the fourth section. The discussion and conclusion will be presented in the last section.

2. The Chaotic Neural Network Model

Let us present a chaotic neural network model briefly [16], [18]. The dynamics of the ith chaotic neuron in the chaotic neural network can be described as follows:

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

$$\eta_i(t+1) = k_f \eta_i(t) + \sum_j w_{ij} x_j(t), \tag{2}$$

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

where the $x_i(t)$ is the output of the ith chaotic neuron at time t, the $\eta_i(t)$ and the $\zeta_i(t)$ are the internal state variables for feedback input from the constituent neurons in the network and the refractoriness of the chaotic neuron at time t, respectively. The functions, $f(\cdot)$ and $g(\cdot)$ are the output function and the refractory function of the neuron, respectively. We take the output function of the neuron $f(x)$ as Sigmoid function with the steepness parameter ε, i.e., $f(x) = 1/(1 + \exp(-x/\varepsilon))$, the refractoriness function as

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$g(x) \equiv x$. The parameter α is the refractory scaling. The parameter a_i is the threshold of the ith neuron. The parameters k_f and k_r are the decay parameters for the feedback inputs and the refractoriness, respectively. The parameters w_{ij} are synaptic weights to the ith constituent neuron from the jth constituent neuron. The neuron does not receive a feedback from itself, i.e., $w_{ii} = 0$.

The weights are defined according to the following symmetric auto-associative matrix of n binary patterns [18]:

$$w_{ij} = \frac{1}{n}\sum_{p=1}^{n}(2x_i^p - 1)(2x_j^p - 1), \quad (4)$$

where x_i^p is the ith component of the pth binary pattern, i.e., $x_i^p = 0$ or 1. In this way, the binary patterns can be stored as basal memory patterns in the network.

3. The Delay Feedback Control Method in the Chaotic Neural Network

Since the pioneer work of Ott et al. (OGY) [21], much attention has been paid to the study of chaos control. Several control methods were put forward, such as occasional proportional feedback control (OPF) [22], delay feedback control (DFC) [20], pinning control [19], [23], phase space constraint control [24], and so on. One usually controls chaos in nonlinear systems for three purposes as follows: (i) To limit a chaotic state into a stable or periodic one; (ii) To let a stable or periodic state become a chaotic one; (iii) To transfer from a certain chaotic state to another. In this paper, we employ the chaos control for the first purpose, that is, to derive a periodic orbit by a control method.

For the first purpose, the control methods can be classified into two categories: feedback control and nonfeedback control. The feedback control methods are primarily devised to control chaos by stabilizing a desired unstable periodic orbit embedded in a chaotic attractor. On the contrary, the nonfeedback control methods suppress chaotic behaviors by converting the system dynamics to a periodic orbit with large perturbations. In both cases, the dynamic structure of the controlled system is different from the original one. In this paper, we focus on the delay feedback control (DFC) method [20]. There are two reasons for us to employ DFC in the chaotic neural network. The first is that the DFC method does not rely on priori knowledge of the local dynamics of the attractor around the unstable periodic orbit (UPO) to be stabilized. The second is that the DFC method does not specify which UPO is to be stabilized.

Now, we propose a novel DFC method focused on the chaotic neural network. According to the original DFC method, the control signal should be added directly to the output of the neurons. Therefore, the output of the neurons in chaotic neural network will be over 1.0 or under 0.0. That is not suitable for chaotic neural network since the outputs of the neurons should be in the range between 0.0 and 1.0. In a chaotic neural network, we therefore have to adapt the DFC method. Considering the output of the neuron being a function of internal state, the output should be different if the internal state changes. We therefore add the control signal to the internal state variable of a neuron instead of injecting control signal directly into output in the original DFC. The delay feedback control is described as follows:

$$x_i(t+1) = f(\eta_i(t+1) + \zeta_i(t+1) + F_i(t+1)), \quad (5)$$

$$F_i(t+1) = K[x_i(t) - x_i(t-\tau)], \quad (6)$$

$$\eta_i(t+1) = k_f\eta_i(t) + \sum_j w_{ij}x_j(t), \quad (7)$$

$$\zeta_i(t+1) = k_r\zeta_i(t) - \alpha x_i(t) + a_i, \quad (8)$$

where $F_i(t)$ is a control signal, K is a control strength, and τ is a delay time coefficient. It should be noted that the parameters of K and τ are important parameters in controlling dynamics, that is, they determine the behaviors of the controlled network and the controllable area of the system.

4. Computer Simulations

4.1 Stored Patterns and Parameters

In this paper, as stored patterns, four patterns as shown in Fig. 1 are employed [18]. Each pattern is composed of 10 by 10 binary pixels, corresponding to the network constructed with 100 neurons. The output of a neuron, x_i, equal to 1, which means the neuron is "excited," is represented by a block "■" in Fig. 1, while the output equal to 0, which means the neuron is "restraining," is denoted by a dot "·."

It is well known that the chaotic neural network gives chaotic dynamics depending on its parameters [16]. We employ $\alpha = 10.0$, $k_r = 0.95$, $k_f = 0.20$ and $a_i = 2.0$ $(i = 1, 2, \cdots, 100)$ in this work. In the case of no control signal, for these parameters, the largest Lyapunov exponent is 0.000280, indicating the network dynamics in chaos.

4.2 Parameter Dependence of Controlled Dynamics

In our simulations, we take one stored pattern (shown in Fig. 1(a)) as the initial state of the network. Computer simulations for the control of chaos are performed according to Eqs. (5)–(8) in which the control feature is determined by the control parameters K and τ. Because of a large amount of dimensions (200 dimensions), it is difficult to characterize the dynamics of the network. In order to overcome the difficulty, we characterize the dynamics by observing the following quantity during long time steps [25],

$$m^p = \frac{1}{N}\sum_{i=1}^{N} x_i(t)\xi_i^p, \quad (9)$$

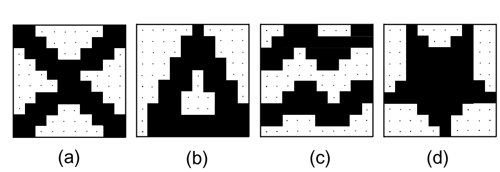

Fig. 1 Four stored patterns.

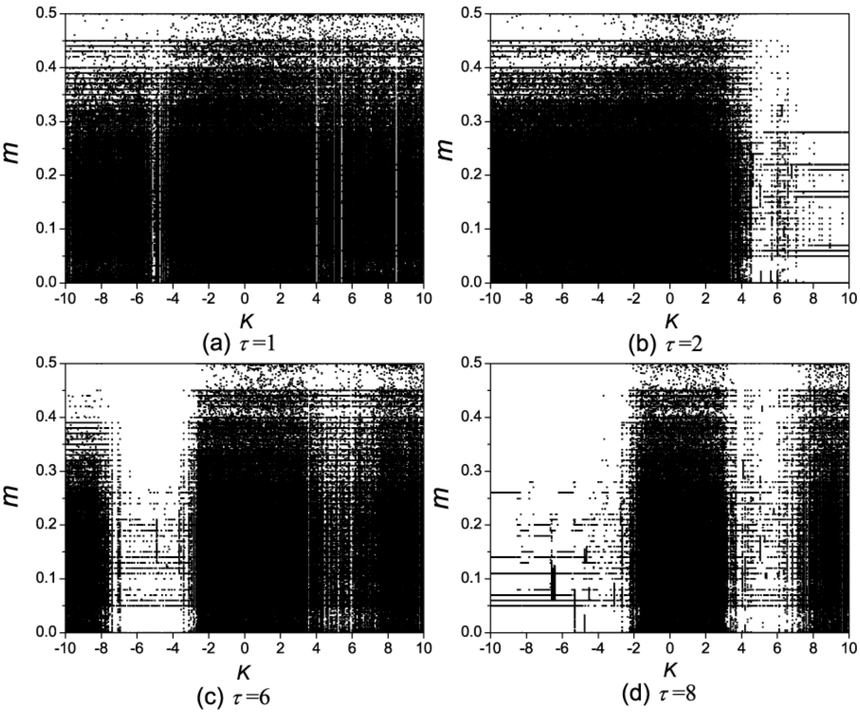

Fig. 2 The long time observation: (a) $\tau = 1$, (b) $\tau = 2$, (c) $\tau = 6$, (d) $\tau = 8$.

where the $x_i(t)$ is the output of the ith neuron of the network at time t, ξ_i^p is the target pattern, and $N = 100$, corresponding to the numbers of the neuron in the network. In this paper, as ξ_i^p, we employ the $p = 1$ pattern. We evaluate $m = m^1$ during the period from $t = 10^4$ to $t = 6 \times 10^4$ with the changing K from -10.0 to 10.0 with 0.1 steps for various τ, and we plot the value of m. In this evaluation, a large number of plotted points show that the controlled dynamics is complicated.

Typical results are given in Fig. 2. In Fig. 2(a), one can observe several "small windows," which indicates that the controlled dynamics are periodic. We obtain similar results for $\tau = 3, 4, 5, 9, 10$ and 13. When τ is 2 (in Fig. 2(b)), a large window is found in positive K. For $\tau = 6$, on the other hand, a large window exists in negative K as shown in Fig. 2(c). When τ is 8 (in Fig. 2(d)), there are large windows in both positive and negative K. We obtain similar results to $\tau = 7$, 11 and 12. Therefore, we conclude that the area in which the dynamics are controlled in periodic orbit depends on the choice of the delay time parameter τ.

4.3 Dynamical Features of Controlled Dynamics among Stored Pattern Space

In this paper, we select τ as 1 for an instance to investigate the controlled dynamical feature in detail for $K = -5.1$, -4.7, 4.0 and 5.4 from Fig. 2(a). Results are similar to the other τ in the window areas.

In order to investigate dynamical properties of the controlled orbit of the chaotic neural network, we employ a visiting measure of the basins of memory attractors [15], [25]. The visiting measure is evaluated by finding out which basins of memory attractors the orbit passes at each time step in the process of controlled and non-controlled dynamics according to the following updating rule,

$$u_i^{(1)} = \sum_{j=1}^{100} w_{ij} z_j^{(0)} + a_i, \tag{10}$$

$$z_i^{(1)} = f(u_i^{(1)}), \tag{11}$$

where the initial condition of Eq. (10) is given by Eq. (5), that is, $z_i^{(0)} = x_i(t)$, which corresponds to the dynamics of the controlled network. According to Eqs. (10) and (11), we check the passing attractor rate at each time step within 5×10^4 time steps from 10^4 time steps to 6×10^4 time steps. Until the first 10^4 time steps, the control signals are not injected, but after that, the control signals are injected. During the next 5×10^4 time steps, the evaluation is performed.

In contrast to the controlled network, the visiting measure of the uncontrolled network is also calculated. The difference between the controlled network and the uncontrolled network is that the initial condition of Eq. (10) is given by Eq. (1) in the uncontrolled network instead of Eq. (5) in the controlled network.

Figure 3 shows the visiting measure of the networks with and without the control signal for $\tau = 1$. One can observe that the visiting measures are quite different for the networks with and without control. Without the control signal, the orbit of the network wanders around all stored patterns and their reverse patterns almost in the same probability. On the contrary, when the network is controlled by the control signal, the orbit of the network is limited to one

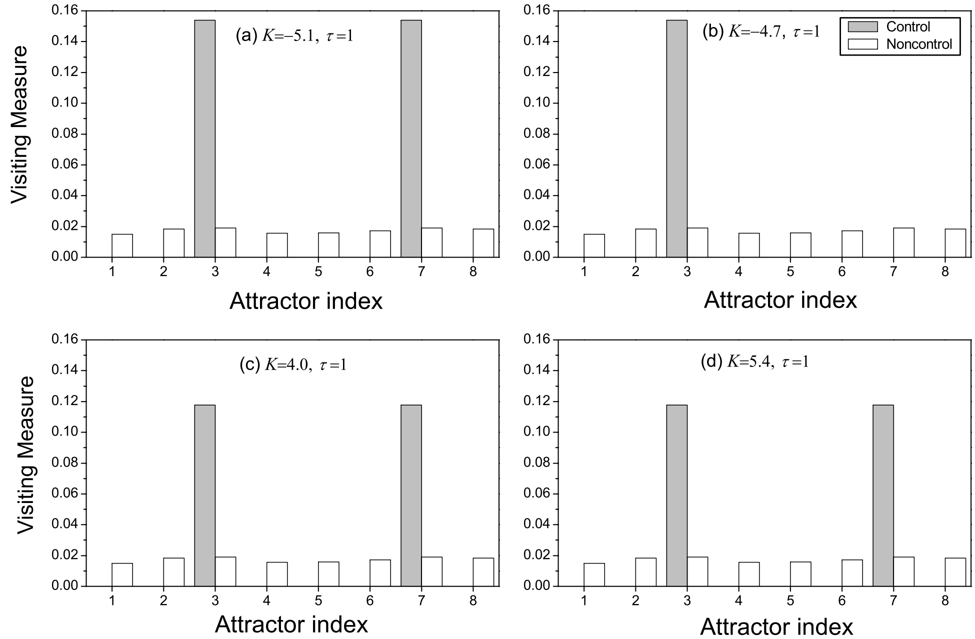

Fig. 3 The measure of visit to the basins of memory attractors of the network with and without control when τ is 1. Visiting probability for $K = -5.1$(a), $K = -4.7$(b), $K = 4.0$(c), $K = 5.4$(d). The horizontal axis denotes the attractors of 4 stored patterns and their reverse patterns. Index 1 to 4 correspond to stored pattern (a) to (d) in Fig. 1, and index 5 to 8 correspond to the reverse patterns of stored pattern (a) to (d), respectively.

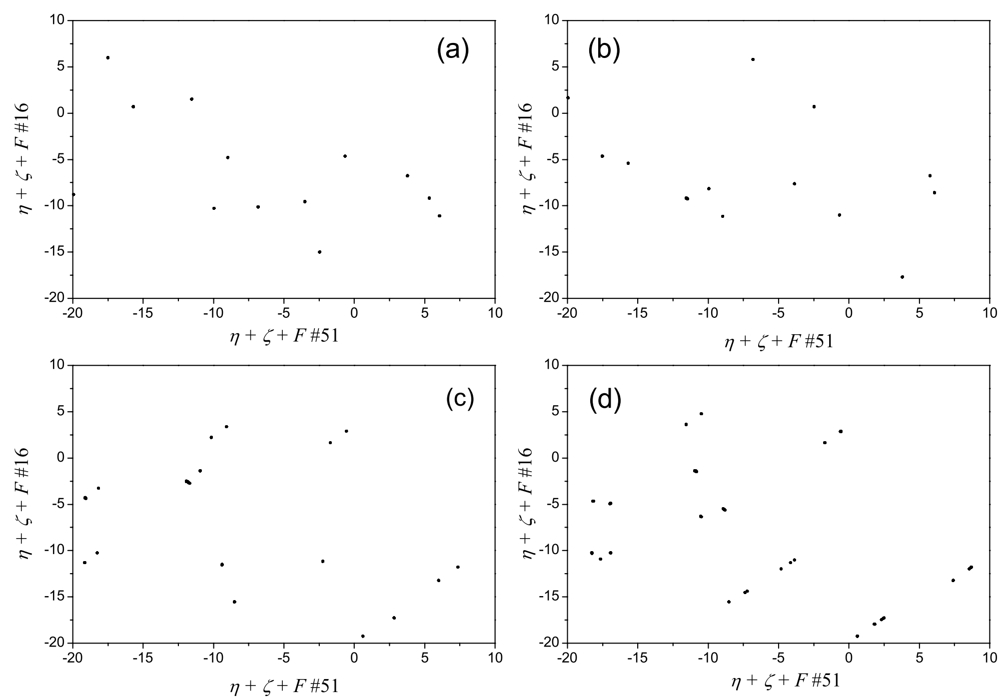

Fig. 4 The two-dimensional plots of internal state variables of the neurons from 4×10^4 to 5×10^4 time steps after control signals are added. The horizontal axis is 51st neuron and the vertical is 16th neuron. In Fig. 4, (a), (b), (c), (d) response to (a), (b), (c), (d) of Fig. 3, respectively.

stored pattern or its reverse pattern. It means that the wandering dynamics of the obit of the network has been localized when the network is controlled by the DFC method.

Next, we investigate whether controlled dynamics are really periodic or not. However, it is difficult to calculate the largest Lyapunov exponent because of the existence of

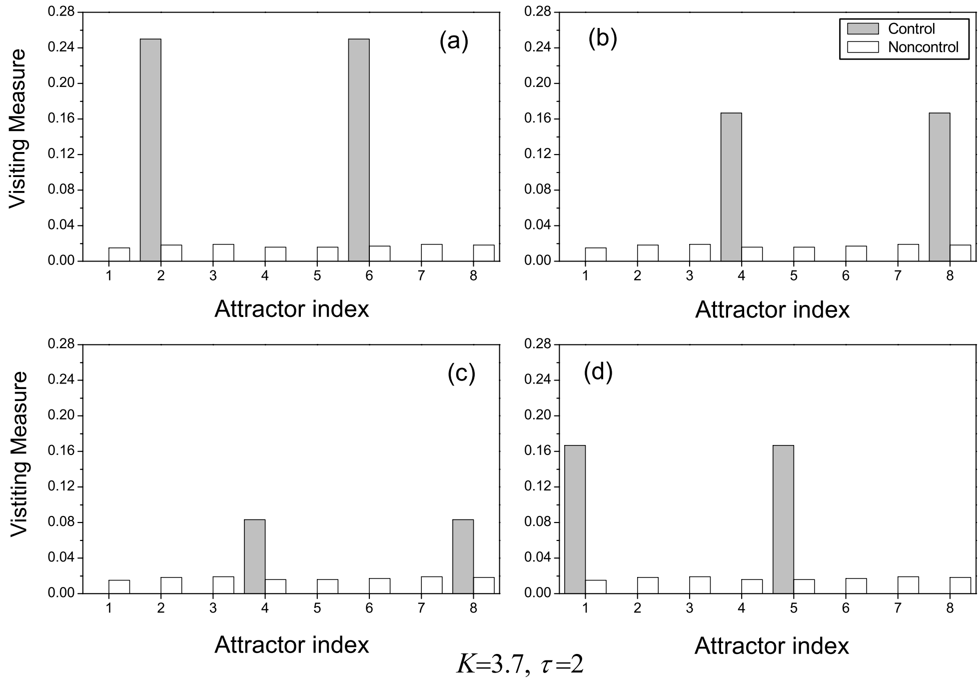

Fig. 5 The probability distributions of visit to the basins of memory attractors of the network with and without control when the moment of the control signal injected is different. K is 3.7 and τ is 2, the control signals are injected at (a) 10^4th time step, (b) 2×10^4th time step, (3) 3×10^4th time step and (d) 4×10^4th time step. In all cases, K is 3.7 and τ is 2. The horizontal axis is as the same as Fig. 3.

the delay feedback control signal. Therefore, we perform a return plot with respect to the internal state variables of 16th neuron and 51st neuron. Results are given in Fig. 4. From Fig. 4, it is clear that the internal state concentrates on some special points within 5×10^4 time steps, that is, the controlled networks are periodic. But the internal states of neurons of controlled networks in the four control parameters are different, which can be deduced from different distributions of those concentrated points. It means that controlled networks in the four control parameters have different orbits though they are in periodic states.

To investigate why the wandering pattern of controlled network is limited in the basins of the 3rd memory attractor and its reverse attractor, we perform another simulations in which the control signals are added at the 10^4th time step, 2×10^4th time step, 3×10^4th time step and 4×10^4th time step when K is 3.7 and τ is 2. The results are given in Fig. 5. Wandering patterns of the controlled network depend on when the control signals are injected. We found that the internal states of the network are different when the control signals are injected. We therefore deduce that the basin of the attractors of the controlled orbit is localized and it depends on the internal state of the network when the control signals are injected into the network.

5. Discussion and Conclusion

Usually, the DFC method can be successfully applied to low dimensional systems. In this paper we apply the method to a high dimensional chaotic neural network model, and propose a DFC method available for a chaotic neural network. The chaotic orbit of the neural network become a periodic orbit wandering around one stored pattern and its reverse pattern by means of our DFC method. But up to now, the fixed point of the network cannot be obtained with the control method. This point deserves further investigation. We investigate dynamics of the periodic orbit controlled by our DFC method in detail by evaluating (i) the long time observation of overlap between controlled dynamics and a certain memory pattern and (ii) the visiting measure of the basin of the memory patterns. Results are as follows:

- The area of periodic dynamics in controlled system depends on the delay time parameter τ.
- Wandering pattern of the controlled network is limited in the basin of a memory attractor and the basin of its reverse attractor.
- On which basin of attractors the controlled orbit is localized depends on the internal state of the network when the control signals are injected into the network.

Adachi and Aihara [18] have explained that the chaotic neural network has the associative dynamics since the synaptic weights of the network are set as those of the conventional auto-associative networks with convergent dynamics. But the refractoriness of the chaotic neuron enable the network to escape from any fixed points and become chaotic. The refractory effect is impaired when the delay feedback signals are injected into the internal states of the chaotic neural network. It enable the network to escape from the chaotic state and enter a periodic orbit. In the paper

[14], in order to accomplish complex memory search, Nara and Davis investigated the adaptability of the chaotic system by means of reinforcement learning. Tsuda [7] showed that asynchronous neural networks gives chaotic itinerancy in memory space in relation to memory search. In order to realize complex memory search among the memory-patterns space, it is important to adapt a certain chaotic orbit into another chaotic orbits or periodic orbits. Thus, our DFC method is one which accomplishes the adaptation. In our investigation, really, the periodic orbits in the chaotic neural network with our DFC control are dependent on the control parameters. But as shown in Figs. 3 and 5, they are a kind of special periodic orbits, which always wander around one stored pattern and its reverse pattern. This work is the first step towards information search by employing associative memory function of the chaotic neural network. We investigated the dynamic of the chaotic neural network with the DFC method in order to explore the relation between control parameters and the dynamics of the controlled network. It is worth for us to improve the DFC method and to achieve the function of information search of associative memory in the chaotic neural network.

The controllable area is meaningfully different and depends on the delay time parameter τ. In order to explain the reason, we made much exploration, such as calculating Poincare section and so on. But we could not give a clear answer. We also calculate the average of self-correlation between the output $x(t)$ of the network and its delay output $x(t-\tau)$,

$$\Phi_{(\tau)} = \left\langle \frac{1}{T} \sum_{t=t_0}^{t_0+T} x_i(t) x_i(t-\tau) \right\rangle, \tag{12}$$

where $\langle \bullet \rangle$ denotes the average among all the neurons. Figure 6 exhibits the result of Φ. From the long time observation of m as shown in Fig. 2(a), the results are similar for $\tau = 1, 3, 4, 5, 9, 10$ and 13. From Fig. 6, on the other hand, the value of Φ is small for $\tau = 3$, 4 and 5, but the value is large for $\tau = 1$, 9 and 10. Up to now, we cannot explain the results of Figs. 2, and it will be our future work.

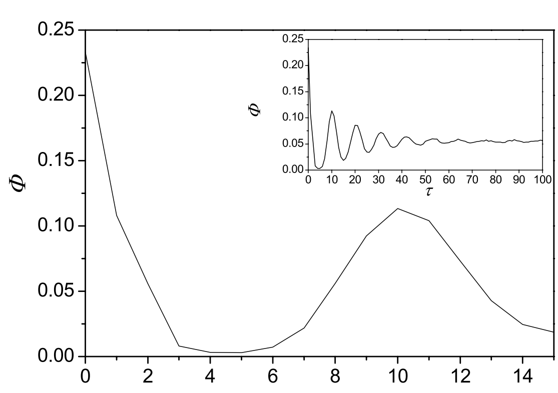

Fig. 6 The self-correlation average of output of the chaotic neural network and its delay output.

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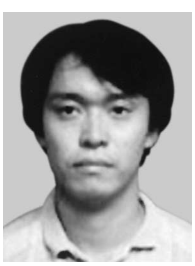

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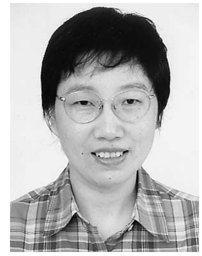

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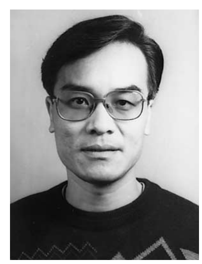

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