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Self-evolution neural model

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Abstract

We discuss a self-evolution neural network. The network is usually in the quiescent chaotic state. When a stimulus is applied, the network jumps into the active thinking state and can recognize the input clearly for a time. As time goes on, the network falls into the multiperiodic state gradually and automatically. At last the network slips into the quiescent chaotic state. The self-evolution behavior of the brain can be simply simulated with this model.

Keywords: Neural network; Chaos; Self-evolution; Hopfield model

1. Introduction

Content-addressable memory neural networks [1-5] have been discussed widely and were introduced to treat some information processing extensively, such as pattern recognition [6,7] or solving combinatorial problems [8]. Understanding the cognition and computing abilities of the human brain is an intriguing problem. The particular attention to the research of chaos in the human brain [9-11] can be explained by the hope that the human memory and consciousness thus might be understood. To simulate the chaotic behavior of the real brain, much research has been done on the existence of chaotic solutions in different neural models [12-21]. Synthesizing the different opinions about the neural network, a more generalized neural network model should possess both the chaotic phenomena and the content-addressable computing ability at least.

Let us consider an ideal reality of the human brain, i.e. the self-evolutional behavior: Usually, the brain stays in the quiescent chaotic state; if stimulated by an external input, such as a picture or a sound, the brain responds to it actively and recognizes it stably; as time goes on, suppose the brain evolves freely, i.e. without self-control, the effect of the stimulus in the brain gradually becomes weaker and vanishes in the end; finally the brain falls into the quiescent chaotic state again. The real neural network not only can process information content-addressably in the active clear state, but also has chaotic behavior in the usual quiescent state.

Can we simulate the self-evolutional behavior of the brain with a model, even in appearance? To our knowledge, little has been published to help answer this question. In Ref. [22] the coupled dynamics of fast spins and slow interactions in neural networks and spin systems are discussed and the transitions between the various phases are observed. The aim of this Letter is to propose a rough self-evolution neural network model. In Section 2 the chaotic network is described simply. The self-evolution neural network model based on it is introduced in Section 3. Here two time scales, i.e. micro-time-scale and macro-time-scale, are defined for the model. With some hypothe-

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ses, the model can work as follows: Usually the network is in a quiescent chaotic state. When a signal put in, the network will jump into the exciting state and associate the input content-addressably for a time. As time goes on, the network will go back to the quiescent chaotic state gradually and automatically. The next section is devoted to the discussion of an example in detail.

2. The chaotic network

In most of the neural models discussed [1-20], the input-output transform functions of the neurons are all supposed to be monotonic, e.g, sigmoid functions. In Ref. [23] it is pointed out that the effective transform functions will take a variety of shapes and should exhibit nonmonotonic behavior. In Ref. [21] a chaotic odd-symmetric nonmonotonic function is discussed,

$$f(x) = \tanh(\alpha x)\exp(-\beta x^2), \tag{1}$$

where $\alpha, \beta \geqslant 0$. With the increasing of β, the iteration dynamics of the function $f(x)$ goes to the chaos through bifurcation.

The N chaotic neurons can compose a chaotic neural network. The dynamics of the ith chaotic neuron is

$$S_i(t+1) = f\left(\sum_{j=1}^{N} J_{ij} S_j(t)\right). \tag{2}$$

Here J is the synaptic connection matrix. One can see that the model becomes the analogue Hopfield model if $\beta = 0$, and becomes the discrete Hopfield model [1] if $\alpha \to \infty$ and $\beta = 0$. Given fixed values for α and β, which are bigger than the thresholds, the network often has chaotic solutions.

As in the usual definition, the neuron is in an active state with $|S| \to 1$, where $S \to 1$ represents positive activation of the signal and $S \to -1$ negative activation, and in a quiescent inhibition state with $|S| \to 0$. So the average activity rate of the neural network can be defined as

$$\rho = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} |S_i(t)|. \tag{3}$$

For large β, the neuron states are more strongly determined by $\exp(-\beta x^2)$ and approach zero, i.e. quiescent states. We call the nonmonotonic exponential β the degree of calm.

One can see that not only chaos but also other features of the brain can be simulated with the model. When the degree of calm $\beta = 0$ or very small, the network falls into the fixed state and the states of neurons $|S| \to 1$. In other words, the network is active and can associate the input correctly. Like the brain in a state of thinking with a high activity and reasonable association ability, the network can be interpreted to be in the clear-headed state. As β increases, bifurcation occurs while ρ decreases. Similar to the brain in the rest state, the network seems to be somewhat in rest and the imaginative faculty is rich. When β further increases, the chaotic solution appears, while ρ approaches zero. We may think that the network with small activity wandering chaotically is in the deep rest state and simulates the sleeping state of the brain in appearance. Actually periodical windows with a low activity rate also appear intermittently in the chaotical region. They are called the dream-time states.

3. The self-evolution neural model

Based on the chaotic neural network discussed in Ref. [21], a self-evolution neural network can be suggested to simulate the self-evolution behavior of the brain in appearance. First two time scales, i.e. micro-time scale and macro-time scale, are defined for the model. The micro-time unit $[\tau]$ is the basic time unit, i.e. the iteration step of the dynamics. The macro-time $[T]$ is an interval of the micro-time,

$$1[T] = n[\tau], \tag{4}$$

where n is an integer. This means that a macro-time unit consists of n micro-time units, i.e. n iteration steps. In other words, macro-time $m[T]$ means micro-time $mn[\tau]$, i.e. $m[T] = mn[\tau]$. The macro-time scale is introduced to reflect the period of change of the degree of calm β, i.e. the self-evolution speed of the network: In the model, we suppose that the degree of calm changes once after each macro-time unit. We know that the process period of a real neuron is of the magnitude of a millisecond. From our experience, the effective association time of the brain responding to an input is of the magnitude of a minute. We can reasonably regard the process period as the micro-time unit, and let the magnitude of the macro-time be the same as that of the effective association time. With this hypothesis, we can let $n = 10^4$.

As mentioned above, the degree of calm β should be changed once each macro-time, i.e. n iteration steps. In order to evolve by itself, the degree of calm β of the model must be a self-adapting parameter of the network and should have an inverse relationship with the average activity rate ρ. So we defined the degree of calm β in macro-time $m[T]$ as determined by the average activity rate of the network at the macro-time $m[T]$, i.e.

$$\beta(m[T]) = F(\rho(m[T])). \tag{5}$$

Here the self-evolution function $F(x)$ should satisfy the following conditions: $F(1) = 0$, $F(0) = k_0$ a positive, and $F(x)$ monotonically decreases with x. Obviously, k_0 is the maximum value of the degree of calm β, and 0 the minimum.

The third hypothesis is that the average activity rate $\rho(m[T])$ is determined by the network during an interval of micro-time before the macro-time $m[T]$, i.e.

$$\rho(m[T]) = \rho(mn[\tau]) = \frac{1}{T_0}\sum_{t=1}^{T_0}\frac{1}{N}\sum_{i=1}^{N}|S_i(mn[\tau]-t)|, \tag{6}$$

where $T_0 < n$.

Now suppose a signal S is put into the network at macro-time $m[T]$, the degree of calm β is adapted by the input signal as

$$\beta = F(\rho_0), \quad \rho_0 = \frac{1}{N}\sum_{i=1}^{N}|S_i|. \tag{7}$$

Viewed from the third hypothesis, Eq. (7) indicates that the input has a continuous effect upon the network during a macro-time unit.

With the above hypotheses, the self-evolution neural network can be working as follows: When an input stimulates the network at time $0[T] = 0[\tau]$, the degree of calm β is defined by the input signal. Because each component of the input is $S_i = \pm 1$, one can obtain $\rho_0 = 1$ and the degree of calm jumps to its minimum value $\beta(0[T]) = 0$. Thus the network becomes the Hopfield model and can recognize the input clearly. At time $1[T]$, the average active degree $\rho(1[T])$ is a little smaller than 1 because of $|\tanh(\alpha x)\exp[-\beta(0[T])x^2]| = |\tanh(\alpha x)| < 1$. So $\beta(1[T])$ is a little larger than $\beta(0[T]) = 0$. Then at the next macro-time $2[T]$, $\rho(2[T]) < \rho(1[T])$ and $\beta(2[T]) > \beta(1[T])$, because of $|\tanh(\alpha x)\exp[-\beta(1[T])x^2]| < |\tanh(\alpha x) \times \exp[-\beta(0[T])x^2]|$. As macro-time increases, the average activity rate ρ decreases and the degree of calm β increases gradually and automatically. This means that the network goes to the multiperiodic state and finally to the quiescent chaotic state gradually and automatically. If another stimulus is put in the network, the same self-evolution course recurs. Obviously, due to the complexity of the brain, the biological mechanism of the self-evolutional behavior of the brain is far from being understood. As a first approach to an answer and for engineering application purposes, it is worth studying this model, even if it is much simpler compared with the real complex brain.

4. An example

To discuss the self-evolution model in a coherent and simple manner, let us use an example to interpret it in detail. Suppose the network consists of six neurons, i.e. $N = 6$. A symmetric synaptic connection with zero diagonal is randomly produced as follows,

$$J = \begin{bmatrix} 0.0 & -0.9 & 0.3 & 0.4 & 0.1 & -0.5 \\ -0.9 & 0.0 & 0.4 & -0.7 & 0.2 & 0.4 \\ 0.3 & 0.4 & 0.0 & -0.4 & -0.5 & -0.2 \\ 0.4 & -0.7 & -0.4 & 0.0 & -0.8 & 0.8 \\ 0.1 & 0.2 & -0.5 & -0.8 & 0.0 & 0.6 \\ -0.5 & 0.4 & -0.2 & 0.8 & 0.6 & 0.0 \end{bmatrix}. \tag{8}$$

When $\alpha \to \infty$, and $\beta = 0$, the model is the discrete Hopfield model [1] in which the following six configurations can be stably stored,

$$\begin{aligned}
&(-1,\ 1,\ 1,-1,-1,-1),\\
&(\ 1,-1,-1,\ 1,\ 1,\ 1),\\
&(\ 1,-1,-1,-1,\ 1,-1),\\
&(-1,\ 1,\ 1,\ 1,-1,\ 1),\\
&(-1,\ 1,-1,-1,\ 1,\ 1),\\
&(\ 1,-1,\ 1,\ 1,-1,-1).
\end{aligned}$$

In the computer simulation, let $\alpha = 6.0$, $T_0 = 1000$ and the self-evolution function of the degree of calm β is

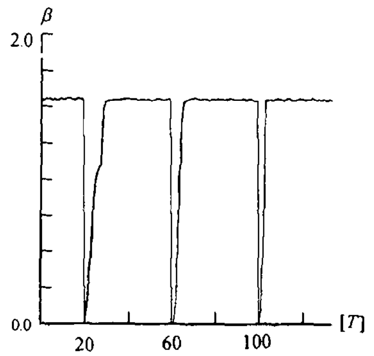

Fig. 1. The curve of the degree of calm β versus the macro-time.

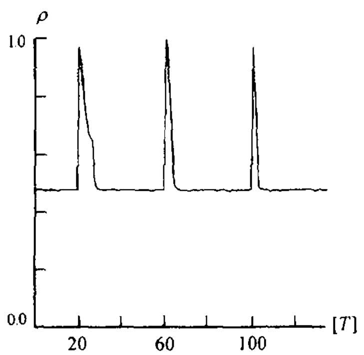

Fig. 2. The curve of the average activity rate ρ versus the macro-time.

$$\beta = 3.7 \ln(2.0 - \rho). \tag{9}$$

Assume the network is in a quiescent chaotic state at first. At macro-time $t = 20[T]$, an input $(-1,1,1,-1,-1,-1)$, which is one of the stored configurations in the Hopfield model case, stimulates the network. The network evolves by itself until the macro-time $t = 60[T]$. Then in comes another input $(1,1,-1,-1,-1,1)$, which is a new configuration compared with the stored patterns. At time $t = 100[T]$, another new configuration $(1,-1,1,1,-1,1)$ is put into the network again.

How does the network evolve automatically with three input signals? In Fig. 1, the curve of the degree of calm β versus the macro-time is drawn. The curve of the average activity rate ρ versus the macro-time is given in Fig. 2. Fig. 1 and Fig. 2 have a determined relationship as in Eq. (9). To investigate the dynamics of the neuron in detail, the values of the first neuron $S_1(t)$ in each iteration (i.e. the micro-time) during

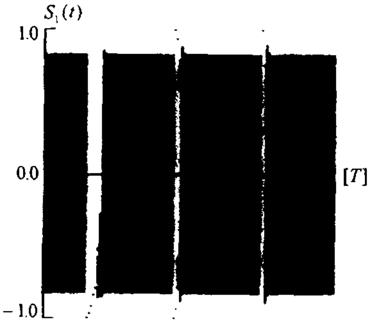

Fig. 3. The values of the first neuron $S_1(t)$ in each iteration during each macro-time unit.

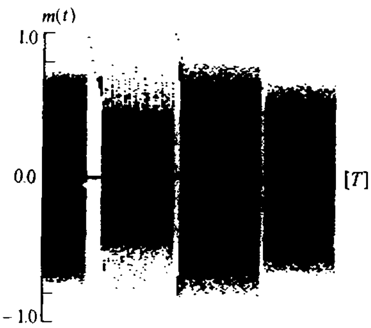

Fig. 4. The dynamics of the overlap $m(t)$ during each macro-time unit.

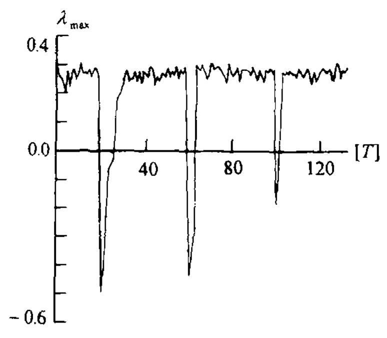

Fig. 5. The curve of the largest Lyapunov index of the model versus the macro-time.

each macro-time unit are shown in Fig. 3. During each macro-time unit, the network iterates n steps, i.e. n micro-time units with a fixed degree of calm $\beta[T]$. To discuss the dynamics of the network, the overlap between the configuration $S(t)$ at micro-time t and the input pattern $S(0)$ is defined as

$$m(t) = \frac{1}{N} \sum_{i=1}^{N} S_i(t)\, S_i(0). \quad (10)$$

In Fig. 4, the dynamics of the overlap during each macro-time unit are drawn. The Lyapunov indexes are the important characteristic exponents for a chaotic system. The curve of the largest Lyapunov index $\lambda_{\max}$ of the model versus macro-time is drawn in Fig. 5.

From Figs. 1–5, one can see that usually the network is in the quiescent chaotic state, in which the average activity rate and the degree of calm are almost fixed in a very small range respectively, i.e. $\rho \simeq 0.48$ and $\beta \simeq 1.55$. At macro-time $20[T]$ a stored signal is put in. The network jumps from a chaotic state to an associative state which has a high average activity rate and a negative largest Lyapunov index. During the following five macro-time units, i.e. fifty thousand iterations, the network can recognize the input correctly. For example, the output of the first neuron is positive, but its value decreases from 1 to about 0.8 with macro-time going from $20[T]$ to $24[T]$. It means that the strength of attention decreases as time passes by. At macro-time $25[T]$, the network falls into the multiperiodic associative state, in which the largest Lyapunov index is negative and the overlap is fixed in a small range around 0.7. One can interpret this as follows. After a long time of concentration of attention, the network seems to be resting and no longer rigorous or strict, i.e. likes to wander periodically among some patterns. At the following macro-time unit, the network takes a step into the small range chaotic state, in which the largest Lyapunov index is positive and the overlap is fixed in a small range around 0.6. After that, the network goes to the state with low average active rate, a large range of overlap and positive Lyapunov index, i.e. to the quiescent chaotic state automatically. Once the network has evolved into the quiescent chaotic state, the average activity rate and the degree of calm of the network are almost fixed in a very small range respectively. At macro-time, i.e. $60[T]$, a new configuration is put in. Although the network transforms into an associative state, it cannot recognize the new signal correctly and singularly. The network takes turns between two patterns. After two macro-time units, the network slides into the multiperiodic associative state during the following macro-time unit, and then into the quiescent chaotic state. At macro-time $100[T]$, another new configuration is put in. Contrasted with the last case, the network goes to a fixed state during the first macro-time unit. In other words, the network can recognize the input to one of the stored patterns correctly and singularly. But after two macro-time units, the network falls into the quiescent chaotic state directly. If we compare the macro-time length in the clear-headed state in the first case with the next two cases, it seems that the network gets a smaller impression with an input with some noise added compared with stored patterns, than with the input which is one of the stored patterns.

5. Conclusion

In this Letter, the self-evolution neural network is discussed. The network is usually in the quiescent chaotic state. When a stimulus comes, the degree of calm of the network becomes zero. The network becomes the Hopfield model and can recognize the input clearly for a time. Sometimes the network can recognize the input correctly. If the input has more noise compared with the stored patterns, the network maybe cannot recognize it correctly. Often the network gets a smaller impression with noise added input. As time goes on, the degree of calm increases gradually and automatically. The strength of attention decreases, i.e. the impression with the input gets weak. After a time, the network falls into the multiperiodic state, while the average activity rate becomes small. One can say that the network is full of imaginative power at this time. The periodic number of free images becomes large, and approaches infinity at last. The average activity rate goes to its smallest level at the same time and the network slips into the quiescent chaotic state. Obviously, due to the complexity of the brain, the biological mechanism of the self-evolution behavior of the brain between computing and chaos is far from being understood. As a first approach to an answer and for engineering application purposes of setting up a neural computer, it is worth studying the model even if it is very simple compared with the real complex brain.

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