Chaotic Neural Network with Radial Basis Function Disturbance

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Chaotic Neural Network with Radial Basis Function Disturbance

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Abstract: This novel chaotic neural network bases on the Chen’s transiently chaotic neural network. It is proposed by introducing radial basis function as disturbance item into the inside state. Analyze the dynamics behavior of the single chaotic neuron and the chaotic search capability of the network. Research the capability of the novel network for resisting the disturbance. This chaotic neural network with radial basis function disturbance is used to solve TSP. The simulation result indicates that this network can avoid the limit of being trapped into the local minima and the capability of resisting the disturbance is perfect.

Key Words: Chaotic neural network, Disturbance, Inside state, Radial basis function

1 INTRODUCTION

Hopfield neural network has been proved to be a powerful tool for solving combinatorial optimization problems and other fields. But Hopfield network is easy to be trapped into the local-minimum whenever it is applied to combinatorial optimization problems. So scholars introduce the global searching character of chaotic dynamics into neural network for avoiding trapping into local minimum and have presented multifarious model of chaotic neural network in a great measure.

Discussing the hardware circuitry then people can observe the dynamics behavior of the chaotic neural network immediately and it can be the base of producing chaotic neural computer. When research the software simulation and hardware realization of the neural network, because the instability of component some hardware is with disfigurement in different degree. Necessarily appear some disturbance to affect the network in the some states. So, the neural computer should possess the capability for resisting the disturbance. This paper presents a new chaotic neural network which is based on the model of the Chen’s transiently chaotic neural network. The novel network is proposed by introducing radial basis function as disturbance item into the inside state. Analyze the dynamics behavior of the single chaotic neuron and research the capability of the novel network for resisting the disturbance. This chaotic neural network with radial basis function disturbance is used to solve TSP. The simulation result indicates that the capability of this network for resisting the disturbance is perfect.

2 MODEL OF CHAOTIC NEURON

The novel network is proposed by introducing radial basis function as disturbance item into the inside state. There are many types of radial basis function, this paper choose Contrary Multiquadric function as disturbance item to change the inside state.

The single neuron model can be described as follows:

\[ x(t) = 1/(1 + \exp(-y(t)/\varepsilon_0)) \]  

(1)

\[ y(t + 1) = ky(t) + f(y(t)) - z(t)(x(t) - I_0) \]  

(2)

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\[ z(t + 1) = (1 - \beta)z(t) \]  \hspace{1cm} (3)

\[ f(u) = \frac{1}{(u^2 + \delta^2)^\alpha} \quad (\alpha > 0) \]  \hspace{1cm} (4)

where \( x(t) \) is the output of the neuron at the time of \( t \); \( y(t) \) is the internal state of the neuron at the time of \( t \);

\( I_0 \) is a positive parameter; \( k \) is a damping factor of nerve membrane \((0 \leq k \leq 1)\); \( \varepsilon_\alpha \) is steepness parameter of the activation function; \( z(t) \) is the self-feedback connection weight; \( \beta \) is the damping factor of \( Z(t) \);

\( f(u) \) is the Contrary-Multiquadric function; \( \delta \) is the spread constant of radial basis function; \( \alpha \) is the parameter of the Contrary-Multiquadric function.

The single neuron can show transiently chaotic dynamics behavior when choosing appropriate value of every parameter. So analyze the dynamics characteristic firstly by the state bifurcation figures and the time evolution figures of the maximal Lyapunov exponent.

In order to make the neuron behave transient chaotic behavior, the parameters are set as follows:

\( \varepsilon_\alpha = 0.25 \quad y(1) = 0.2 \quad z(1) = 0.5 \quad k = 0.8 \quad I_0 = 0.35 \quad \delta = 0.9 \quad \alpha = 10. \)

The state bifurcation figures and the time evolution figures of the maximal Lyapunov exponent are shown as Fig.1~Fig.2 when \( \beta = 0.0004 \).

![Fig.1 State bifurcation figure of the neuron](image1)

![Fig.2 Time evolution figure of the maximal Lyapunov exponent](image2)

Seen from the above state bifurcation figures and the time evolution figures of the maximal Lyapunov exponent, the neural network behaves a transient chaotic dynamic behavior. The network will be stable equilibrium state by \( z(t) \) decrease continuously as seen from the reversed bifurcation figure. This network can avoid to be trapped into the local minima because chaotic search possesses inside stochastic and orbit traverse property. The stochastic property ensures search capability in expansive range, and the orbit traverse...
property ensures the system can traverse all possible state not repeatedly. The network is controlled by the
dynamics which is grads decreasing at the end of transiently chaotic dynamics behavior. Finally, the novel
network will be stable equilibrium state like Hopfield neural network.

Now analyze the effect of spread constant. In order to make the neuron behave transient chaotic behavior,
the parameters are set as follows:

$$\epsilon_0=0.25 \quad y(1)=0.2 \quad z(1)=0.5 \quad k=0.8 \quad I_0=0.35 \quad \beta=0.0004 \quad \alpha=10$$

The state bifurcation figures and the time evolution figures of the maximal Lyapunov exponent are shown
as Fig.3~Fig.4 when $\delta=0.92$.

![Fig.3 State bifurcation figure of the neuron](image1)

![Fig.4 Time evolution figure of the maximal Lyapunov exponent](image2)

Seen from the above state bifurcation figures and time evolution figure of the maximal Lyapunov exponent
show as Fig.5~Fig.8, the spread $\delta$ affect the dynamics behavior of the chaotic neuron powerfully. The
difference of the value is only 0.03 when $\delta=0.92$ and $\delta=0.95$, but the difference of time is wide as seen as
the time evolution figure of the maximal Lyapunov exponent. The search area is longer and the speed of
convergence is slower when $\delta$ is smaller. Contrarily the search area is shorter and the speed of convergence is
faster when $\delta$ is bigger. It illuminates that the Contrary Multiquadric function is more selected as the width
$\delta$ is smaller and the disturbance capability of radial basis function is stronger, but the disturbance capability of
radial basis function is thinner as the width $\delta$ is bigger.

3 MODEL OF CHAOTIC NEURAL NETWORK

Based on the Chen’s transiently chaotic neural network and the novel chaotic neuron model mentioned
above, add the Contrary Multiquadric function as the disturbance item to the inside state.

The novel chaotic neural network with radial basis function disturbance is described as follows:

$$x(t) = 1 / (1 + \exp(-y(t) / \epsilon_0)) \quad (5)$$
\[ y_i(t+1) = ky_i(t) + f(y(t)) + \gamma \left( \sum_{j \neq i} w_{ij} x_j(t) + I_i \right) - z_i(t)(x_i(t) - I_o) \]  
\[ z_i(t+1) = (1-\beta)z_i(t) \]  
\[ f(u) = \frac{1}{(u^2 + \delta^2)^{\alpha/2}} \quad (\alpha > 0) \]

Where \( i = 1, 2, 3, \ldots, n \) is the index of neurons and \( n \) is the number of neurons; \( x_i(t) \) is the output of neuron \( i \); \( y_i(t) \) is the internal state for neuron \( i \); \( z_i(t) \) is the self-feedback connection weight; \( \beta \) is the simulated annealing parameter; \( w_{ij} \) is the connection weight from neuron \( j \) to neuron \( i \), \( w_{ii} = 0 \); \( I_i \) is the input bias of neuron \( i \); \( \varepsilon_0 \) is the steepness parameters of the activation function; \( k \) is the damping factor of the nerve membrane, \( 0 \leq k \leq 1 \); \( \gamma \) is the positive scaling parameter for inputs; \( I_o \) is a positive parameter; \( \delta \) is the spread constant or width of the radial basis function; \( \alpha \) is the parameters of the Contrary Multiquadric function.

The dynamics of chaotic neural network depend on the value of \( k \), \( \gamma \), \( z_i(t) \) and \( z(t) \) sensitively. Parameter \( k \) expresses the capability of the network to reserve or forget the inside state. The capability for reserving the inside state is stronger when \( k \) is bigger, and the capability for forgetting the inside state is stronger when \( k \) is smaller. \( z(t) \) is dynamically decreasing, this variable corresponds to the temperature in the usual stochastic annealing process, the speed of annealing depends on the parameter \( \beta \), and the network finally converges to a stable equilibrium state by \( z(t) \) becoming small step by step. Item \( \beta \) decreases faster as \( \beta \) is bigger, but the chaotic search capability of the network can not be utilized adequately. Item \( \beta \) decreases slower as \( \beta \) is smaller, but the speed of convergence will be affected. The effect of parameter \( \gamma \) is also very important, which expresses the influence of energy function to dynamics. The influence of the energy function is too strong if \( \gamma \) is too big. The network will converge so fast that transiently chaotic state cannot be gained and the network is easy to be trapped into the local minima. The influence of the energy function is too faint if \( \gamma \) is too small. Although the transiently chaotic state can be gained, it can not converge to the optimal solution. The parameters must be set to suitable value when solving combinational optimization problem to express the advantage of the chaotic neural network in solving this type of problem.
4 APPLICATION TO TRAVELING SALESMAN PROBLEM

The Traveling Salesman Problem (TSP) is a classically combinational optimization problem and is a NP-hard problem, and there is no effective way to solve this problem at present. This paper applies the novel chaotic network with radial basis function disturbance to TSP.

TSP can be described as follows: To confirm a shortest path and need to visit every city only once when known N cities and the distance between two cities. A solution of TSP with N cities is represented by N×N-permutation matrix, where each entry corresponds to output of a neuron in a network with N×N lattice structure. Assume vxi to be the neuron output which represents city x in visiting order i. Assume dxy to be the distance between city x and city y. Because the symmetry of the determinant, coefficient A=B, and a global shortest value of E expresses a shortest effective path. A computational energy function which is to minimize the total tour length while simultaneously satisfies all constrains takes the follow form (1):

\[ E = \frac{A}{2} \sum_{x=1}^{n} \left( \sum_{i=1}^{n} V_{xi} - 1 \right)^2 + \frac{B}{2} \sum_{i=1}^{n} \left( \sum_{x=1}^{n} V_{xi} - 1 \right)^2 + \frac{D}{2} \sum_{x=1}^{n} \sum_{y=1}^{n} \sum_{i=1}^{n} d_{xy} V_{xi} V_{yi} + I_1 \]

The parameters of the network are set as follows:

\[ \epsilon_0 = 0.25 \] , \[ z(1) = 0.5 \] , \[ k = 0.8 \] , \[ I_0 = 0.35 \] , \[ \beta = 0.0004 \] , \[ \gamma = 0.5 \] , \[ \alpha = 10 \] , \[ \sum_{j \neq i}^{n} W_{j}(t) + I_1 = 0.001 \] , \[ y(1) = 3 \].

The curve for the change of \( y(t) \) when choose different \( \delta \) is shown as Fig.5-Fig.6.

![Fig.5 The curve for the change of \( y(t) \) when \( \delta = 0.5 \)](image1)

![Fig.6 The curve for the change of \( y(t) \) when \( \delta = 0.7 \)](image2)

Seen from Fig.5-Fig.6, the selectivity of the Contrary Multiquadric function is clearer and the disturbance is stronger when \( \delta \) is smaller. The strong disturbance can affect the input of the network and the input will be enlarged. Indeed, it will affect the chaotic search capability of the network and can not converge to the global minima.

The parameters of the network are set as follows:

\[ \epsilon_0 = 0.2 \] , \[ z(1) = 0.5 \] , \[ k = 1 \] , \[ I_0 = 0.9 \] , \[ \beta = 0.0013 \] , \[ \gamma = 0.8 \] , \[ \alpha = 10 \]

Research the effect of the different \( \delta \) to solve TSP. The results of 200 different internal conditions for each \( \delta \) are summarized in Table 1. The column ‘NLP’, ‘NOP’, ‘RLP’ and ‘RGM’ respectively represents the number of legitimate path, the number of optimal path, the rate of legitimate path, the rate of global minima, and
the rate of local minima.

<table>
<thead>
<tr>
<th>δ</th>
<th>α</th>
<th>NLP</th>
<th>NOP</th>
<th>RLP</th>
<th>RGM</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.9</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.8</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.7</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.6</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.5</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.4</td>
<td>10</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.3</td>
<td>10</td>
<td>194</td>
<td>191</td>
<td>97%</td>
<td>95.5%</td>
</tr>
<tr>
<td>0.25</td>
<td>10</td>
<td>199</td>
<td>178</td>
<td>99.5%</td>
<td>89%</td>
</tr>
<tr>
<td>0.24</td>
<td>10</td>
<td>150</td>
<td>19</td>
<td>75%</td>
<td>9.5%</td>
</tr>
</tbody>
</table>

As seen from Table1, the rate of legitimate path and the rate of optimal path are 100% in the state of $\delta \geq 0.4$ when $\alpha = 10$ is changeless, but both the rate of legitimate path and the rate of optimal path are decreased obviously as $\delta \leq 0.4$. It can explain that the capability of the novel chaotic network for resisting disturbance is very strong when $\delta \geq 0.4$, so the network can converge to the global minima with 100% rate of optimal path. The disturbance of the Contrary Multiquadric function is stronger as $\delta$ changes to be smaller. The capability of the network for resisting disturbance decreases little as $0.3 \leq \delta \leq 0.33$. The disturbance of the Contrary Multiquadric function change to be stronger obviously and the capability of the network for resisting disturbance decreases also obviously as $0.24 \leq \delta < 0.3$. So, for assuring the novel network to solve TSP optimally, the parameter $\delta$ should be controlled above 0.4.

The parameters of the network are set as follows:

$\varepsilon_0 = 0.2 \quad z(1) = 0.5 \quad k = 1 \quad I_0 = 0.9 \quad \beta = 0.0013 \quad A = 1 \quad D = 1 \quad \gamma = 0.8 \quad \delta = 0.33$

Research the effect of the different $\alpha$ to solve TSP. The results of 200 different internal conditions for each $\alpha$ are summarized in Table2.

<table>
<thead>
<tr>
<th>δ</th>
<th>α</th>
<th>NLP</th>
<th>NOP</th>
<th>RLP</th>
<th>RGM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.33</td>
<td>50</td>
<td>200</td>
<td>200</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>0.33</td>
<td>30</td>
<td>199</td>
<td>199</td>
<td>99.5%</td>
<td>99.5%</td>
</tr>
<tr>
<td>0.33</td>
<td>10</td>
<td>197</td>
<td>196</td>
<td>98.5%</td>
<td>98%</td>
</tr>
<tr>
<td>0.33</td>
<td>5</td>
<td>185</td>
<td>175</td>
<td>92.5%</td>
<td>87.5%</td>
</tr>
<tr>
<td>0.33</td>
<td>3</td>
<td>176</td>
<td>147</td>
<td>88%</td>
<td>73.5%</td>
</tr>
<tr>
<td>0.33</td>
<td>2</td>
<td>175</td>
<td>137</td>
<td>87.5%</td>
<td>68.5%</td>
</tr>
</tbody>
</table>

As seen from Table2, the rate of legitimate path and the rate of optimal path are 100% in the state of
$\alpha \geq 40$ when $\delta = 0.33$ is changeless, the network have stronger capability for resisting disturbance and can converge to the optimal result fast. Both the rate of legitimate path and the rate of optimal path are decreased continually when $\alpha \leq 30$. The rate of optimal path decrease fast when $\alpha < 10$ and the network nearly can not find the optimal path as $\alpha = 1$. It indicates that the capability of the Contrary Multiquadric function for resisting disturbance is stronger by stronger, the affection to the inside state is bigger and bigger, and the novel chaotic network is not easy to converge to the optimal solution. So, the parameter $\alpha$ should be set above 30 in the state of other parameters are changeless for assuring the novel network to solve TSP optimally.

5 CONCLUSION

In this paper, it introduces radial basis function as disturbance item into the inside state bases on the Chen’s transiently chaotic neural network. Analyze the dynamics behavior of the novel chaotic neural network with radial basis function disturbance and use this network to solve combinatorial optimization problems. The simulation result indicates that this network also can solve TSP with high precision compare with the Chen’s chaotic neural network as the disturbance is not very strong. This novel network is proved with higher capability for resisting disturbance.

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