International Journal of Grid Distribution Computing
Vol.8, No.1 (2015), pp.159-168
http://dx.doi.org/10.14257/ijgdc.2015.8.1.15

Simulation Study on Parameters of SLF Chaotic Neural Network Model

Yonggang Ye

School of Basic Science, Harbin University of Commerce
Harbin Heilongjiang
China
Ye_yonggang@163.com

Abstract

A novel chaotic-neuron model is presented by introducing the non-monotonous activation function which is composed of the Legendre function and the Sigmoid function. The reversed bifurcation of the chaotic neuron model is given and analyzed, meanwhile, how do parameters influence the network convergence speed is discussed. Based on the neuron model, the piecewise simulated annealing SLF chaotic neural network was made by introducing the simulated annealing idea, the model improve the convergence speed, at the same time, the precision of this network have not being influenced. The simulation experiment of function optimization and TSP problem verify the effectiveness of the segmented simulated annealing strategy.

Keywords: *Chaotic neuron network; Legendre function; function optimization; TSP problem;*

1. Introduction

Hopfield proposed discrete stochastic Hopfield neural network model in 1982[1] and presented a continuous model of neural networks in 1984[2], It is the first time to successfully solve the traveling salesman problem by neural network model. By introducing chaotic dynamics in the Hopfield neural network, in 1990, Aihara put forward a chaotic neutral network model [3]. On the basis of Aihara's chaotic neural network model, Chen made more famous Chen's Chaotic Neural Network model[4], in this model, the activation function of Sigmoid is a monotonically increasing function . Inoue constructed chaotic neural network model with resonators [5]. A. Potapove in the paper[6] pointed out that if the chaotic neuron activation function is non-monotonic function, the single neuron can quickly perform chaotic search. Shuai put forward that an effective incentive function should be different forms and should exhibit chaotic behavior [7], In the domestic, Some scholars have made some chaotic neural network models[8-15] that has been successfully used to solve the combinatorial optimization problems. In this paper, a new transient chaotic neural network model is proposed. In this model we have chosen nonlinear function which is composed of Legendre functions and Sigmoid function as a new incentive function, it maintain the advantages of Sigmoid function and Legendre function, meanwhile, it is also a non-monotonic function. After a analysis the effect of combinational parameter and annealing parameter on the convergence rate, annealing strategy has been put forward, the optimization simulation experiment test that the SLF chaotic neural network with piecewise simulated annealing strategy is more effective to solve optimization problems.

ISSN: 2005-4262 IJGDC

2. SLF Chaotic Neuron Model and the Impact of Parameter

Numerous studies show that the optimization algorithm with global optimization capacity is not good enough, it should also have the ability of global optimization and local optimization ability. Legendre function is non-monotonic and has stronger approximation ability, based on Legendre function, establish the following transient neuron model referred to as SLF model.

2.1. SLF Chaotic Neurons Model

Construct a new transient chaos neuron model, in the model, let the combination function of the Legendre function and the Sigmoid function is excitation function, and the model is as follows:

$$x(\mathrm{t}) = f(y(\mathrm{t})) \tag{1}$$

$$y(\mathrm{t}+1) = ky(\mathrm{t}) - z(\mathrm{t})(x(\mathrm{t}) - I_0) \tag{2}$$

$$z(\mathrm{t}+1) = (1-\beta)z(\mathrm{t}) \tag{3}$$

$$f(u) = \begin{cases} \lambda \mathrm{S}(u) + (1-\lambda)(\mathrm{P}_3(u)/2 + 1/2) & -1 \le u \le 1 \\ \mathrm{S}(u) & \text{other cases} \end{cases} \tag{4}$$

$$\mathrm{S}(u) = 1/(1+\exp(-u/\varepsilon_0)) \tag{5}$$

$$\mathrm{P}_3(u) = (5x^3 - 3x)/2 \tag{6}$$

Where $x(t)$ is the output of the neuron at the time of t; $f(u)$ is the excitation function of model; $y(t)$ is the internal state of the neuron at the time of t; I_0 is a positive parameter; k show the neuron's ability to retain internal state($0 \le k \le 1$); ε_0 is steepness parameter of the activation function; $z(t)$ is the self-feedback connection item; β is the annealing parameter of $z(t)$; λ is the combination parameter of excitation function ($0 \le \lambda \le 1$).

2.2. Effects of Combination Parameters on the Convergence Rate

Chaotic dynamical behavior of neurons can be reversed via bifurcation study, in the model, Take n = 3 combination of Legendre functions and Sigmoid function as excitation function. The parameters are set as follows: ε_0 =0.02, $y(1)$ =0.1, $z(1)$ =0.98, k =1, I_0 =0.56, β =0.001,the state bifurcation figures are respectively shown as Fig.1~Fig.3 when λ =1/3, λ =1/2, λ =2/3.

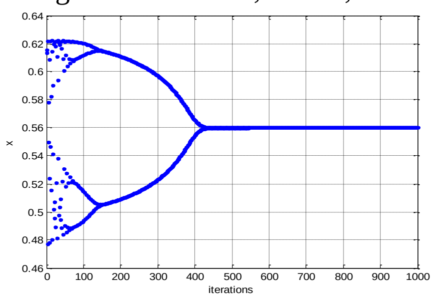

Figure 1. Bifurcation Figure of the Neuron State when λ =1/3

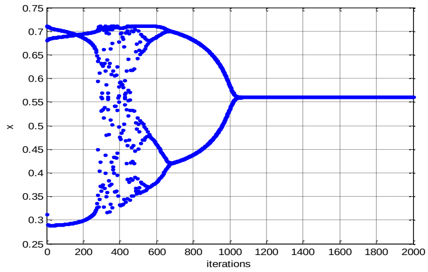

Figure 2. Bifurcation Figure of the Neuron State when λ=1/2

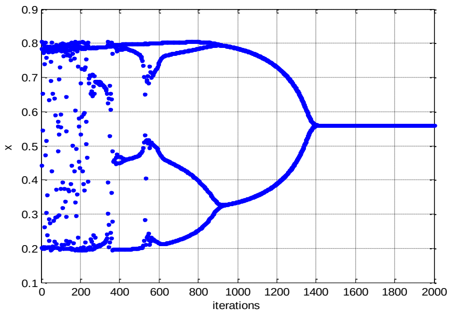

Figure 3. Bifurcation Figure of the Neuron State when λ=2/3

It is easy to draw the following conclusions according to above figures:

(1) The neuron model has transient chaotic dynamical behavior, as to the randomness and ergodicity of chaos search track, neuronal network model can be avoided to converge to a local minimum.

(2) The parameter values of excitation function affect the speed of the network exit chaotic state, the larger the value of λ, the slower speed to exit chaotic state, on the contrary, the chaotic state of the network faster exit. This model has better convergence rate than the Chen-Aihara chaotic neural network.

2.3. Effects of Annealing Parameters on the Convergence Rate

Construct a new transient chaos neuron model, in the model, let the combination function of the Legendre function and the Sigmoid function is excitation function, and the model is as follows:

Let ε_0=0.02, $y(1)$=0.1, $z(1)$=0.98, k=1, I_0=0.56, λ=1/2, the state bifurcation figures are respectively shown as Fig.4~Fig.5 when β=0.002, β=0.004.

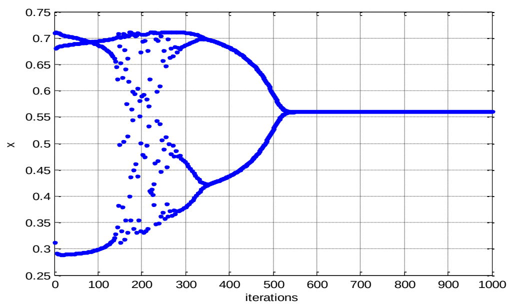

Figure 4. Bifurcation Figure of the Neuron State when β=0.002 λ=1/2

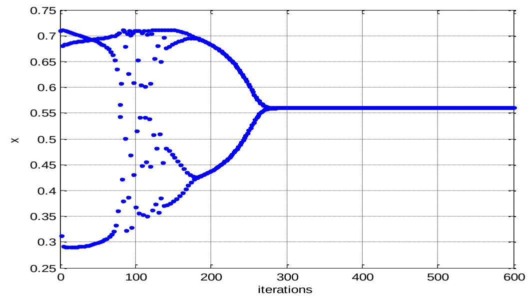

Figure 5. Bifurcation Figure of the Neuron State when β =0.004 λ =1/2

According to above figures, neuron is chaotic state initially, when z_i decline to a certain extent, neuron exit chaotic state through the process of reverse bifurcation, and enter gradient search phase, the higher the value of β, the faster the speed of chaotic neurons exit chaotic stage.

When the value of β is greater, the speed of algorithm converges is fast, but not take full advantage of the dynamic characteristics of chaos, it is easy to fall into local minimum. Conversely, when the value of β is smaller, the speed of algorithm converges is slow. So the piecewise simulated annealing method would be lead into SLF chaotic neuron model.

3. SLF Chaonic Network Model with Piecewise Simulated Annealing Strategy

Pull in the piecewise simulated annealing method in SLF chaotic neuron model, meanwhile, propose a SLF chaotic network model with piecewise simulated annealing strategy is as follows:

$$x_i(\mathrm{t}) = f(y_i(\mathrm{t})) \tag{7}$$

$$y_i(\mathrm{t}+1) = ky_i(\mathrm{t}) + \gamma\left[\sum_{\substack{j=1\\ j\neq i}}^{n} w_{ij}x_j(\mathrm{t}) + I_i\right] - z_i(\mathrm{t})(x_i(\mathrm{t}) - I_0) \tag{8}$$

$$z_i(\mathrm{t}+1) = \begin{cases}(1-\beta_1)z_i(\mathrm{t}), & z(t) > z(0)\varepsilon_1\\ (1-\beta_2)z_i(\mathrm{t}), & z(t) \le z(0)\varepsilon_1\end{cases} \tag{9}$$

$$f(u) = \begin{cases}\lambda \mathrm{S}(u) + (1-\lambda)(\mathrm{P}_3(u)/2+1/2) & -1 \le u \le 1\\ \mathrm{S}(u) & \text{other cases}\end{cases} \tag{10}$$

$$\mathrm{S}(u) = 1/(1+\exp(-u/\varepsilon_0)) \tag{11}$$

$$\mathrm{P}_3(u) = (5x^3 - 3x)/2 \tag{12}$$

Where $x_i(t)$ is the output of neuron i; $f(u)$ is the excitation function of model; $y_i(t)$ is the internal state for neuron i; w_{ij} is the connection weight from neuron j to neuron i, $w_{ij} = w_{ji}$, w_{ii} =0; I_i is the input bias of neuron i; I_0 is a positive parameter; β_1 and β_2 are the simulated annealing parameters, and $\beta_1 < \beta_2$; ε_1 is segmentation parameters($0 \le \varepsilon_1 \le 1$), when $\varepsilon_1 = 0$, the speed of annealing depends on β_1, when $\varepsilon_1 = 1$, the speed of annealing depends on β_2, only when $0 < \varepsilon_1 < 1$, the neuron model is based segmented ideas, the speed of annealing depends on β_1 and β_2 ; $z_i(t)$ is self-feedback connection term, its value is constantly decreasing with the changes of simulated annealing parameters; ε_0 is the steepness parameters of the activation function; k show the neuron's ability to retain internal state($0 \le k \le 1$); γ is a positive scale input parameters, representing the impact of the energy function to chaotic dynamics; λ is the combination parameter of excitation function ($0 \le \lambda \le 1$).

4. The Applications of SLF Chaotic Neural Network with Piecewise Simulated Annealing Strategy

Author names and affiliations are to be centered beneath the title and printed in Times New Roman 12-point, non-boldface type. Multiple authors may be shown in a two or three-column format, with their affiliations below their respective names. Affiliations are centered below each author name, italicized, not bold. Include e-mail addresses if possible. Follow the author information by two blank lines before main text.

4.1. Application of Model in Function Optimization

As in this heading, they should be Times New Roman 11-point boldface, initially capitalized, flush left, with one blank line before, and one after.
Select the following optimization function [14]

$$f(x_1,x_2)=(x_1-0.7)^2[(x_2+0.6)^2+0.1]+(x_2-0.5)^2[(x_1+0.4)^2+0.15] \tag{13}$$

The minimum value of function is 0, the minimum point of function is (0.7, 0.5), the local minimum points are (0.6, 0.4) and (0.6, 0.5).

Utilizing SLF chaotic neural network model[15] that is called model I to solve optimization function, let ε =0.02, k =1, γ =0.05, I_0 =0.56, $z_1(1)$ = $z_2(1)$ =0.98, $y(1)=0.383$, $y(2)=0.283$, and λ=1/2, β =0.002, The evolution of the energy function and the time evolution figure of x_1 and x_2 are shown in Figure 6~7.

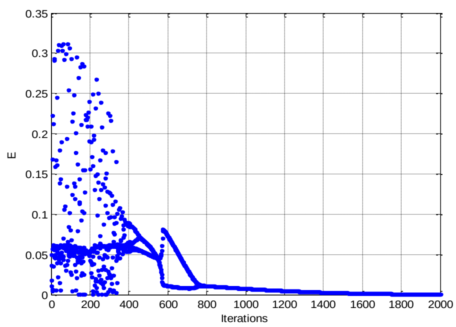

Figure 6. Evolution Figure of the Energy Function in Model I

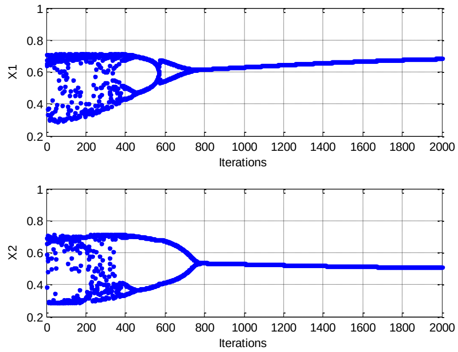

Figure 7. Evolution Figure of x_1 and x_2 in Model I

Utilizing SLF chaotic network model with piecewise simulated annealing strategy that is call model II to solve optimization function. Let ε_0 =0.02, ε_1 =0.5, k =1, γ =0.05, I_0 =0.56, $y(1)=0.383$, $y(2)=0.283$, $z_1(1)$ =0.98, $z_2(1)$ =0.98, and λ=$1/2$, β_1 =0.002, β_2 =0.004, The evolution of the energy function and the time evolution figure of x_1 and x_2 are shown in Figure 8~9.

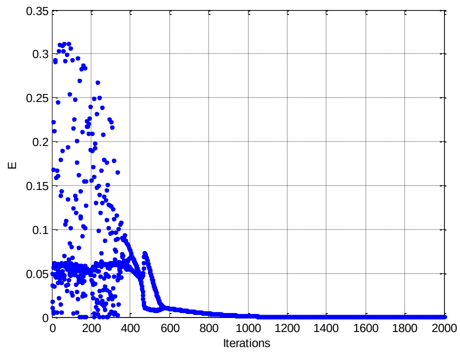

Figure 8. Evolution Figure the Energe Function in Model II

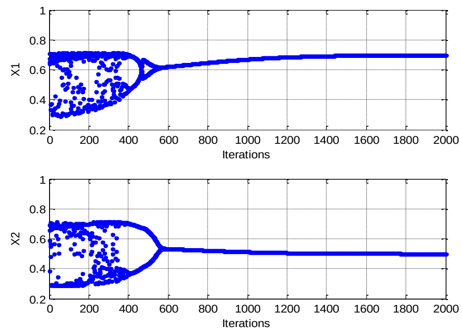

Figure 9. Evolution Figure of the x_1 and x_2 in Model II

In order to compare the two models, take respectively the number of iterations is 600,800,1000,1500,2000, the value of the energy function and the values of x_1 and x_2 are shown in Table 1, n is the number of iterations.

Figure 10. The Comparison of Two Models

	Model I		
	E	x_1	x_2
n=600	0.0726	0.5451	0.6733
n=800	0.0110	0.6173	0.5351
n=1000	0.0076	0.6309	0.5292
n=1500	0.0022	0.6625	0.5157
n=2000	$4.3845*10^{-4}$	0.6832	0.5069
	Model II		
	E	x_1	x_2
n=600	0.0100	0.6208	0.5336
n=800	0.0043	0.6477	0.5220
n=1000	0.0014	0.6701	0.5124
n=1500	$3.9655*10^{-5}$	0.6949	0.5021
n=2000	$7.7863*10^{-7}$	0.6993	0.5003

It is easy to know from figure 6 to 9 and table I : When seeking the optimal value of function Utilizing Model I and model II, although both of two models are able to get the optimal solution, but the model II has obvious advantages.

4.2. Application of Model in Combination Optimization (TSP)

The Traveling Salesman Problem(TSP) is a classically combinational optimization problem and is a NP-hard problem, Symmetric TSP problem with n cities possible have $(n-1)!/2$ paths, Find an effective way to solve this problem is the target of many scholars over the years. 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.

The energy function takes the following form:

$$E=\frac{A}{2}\sum_{i=1}^{n}(\sum_{i=1}^{n}x_{ij}-1)^2+\frac{B}{2}\sum_{j=1}^{n}(\sum_{i=1}^{n}x_{ij}-1)^2+\frac{D}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}d_{ik}x_{ij}(x_{k,j+1}+x_{k,j-1}) \quad (14)$$

In the above formula, d_{xy} represent the distance between city x and city y. Due to the symmetry, equation A=B is hold, and a global shortest value of E expresses a shortest effective path.

In the paper, adopts the following 10-city unitary coordinates: (0.4, 0.4439); (0.2439, 0.1463); (0.1707, 0.2293); (0.2293, 0.716); (0.5171,0.9414); (0.8732, 0.6536); (0.6878, 0.5219); (0.8488, 0.3609); (0.6683, 0.2536); (0.6195, 0.2634). Select the energy function (14), utilizing SLF chaotic neural network model with piecewise simulated annealing strategy, and the parameters of the network are choice as follows: $A=B=1$, $D=2$, $\gamma=0.25$, $k=1$, $I_0=0.5$, $\varepsilon_0=0.02$, $\beta_1=0.002$, $z(1)=0.8$. The simulation results of 100 different internal conditions with different β_2 and ε_1 are summarized in Table II. The Abbreviation NLP, NOP, RLP, RGM and ANI respectively represents the number of legitimate path, the number of optimal path, the rate of legitimate path, the rate of global minima, the average number of iterations.

ε_1	β_2	NLP	NOP	RLP	RGM	ANI
0	-	100	89	100%	89%	1308
0.5	0.002 0.003	100 97	91 92	100% 97%	91% 92%	1015 983
0.6	0.002 0.003	99 96	88 89	99% 96%	88% 89%	959 901
0.8	0.002 0.003	99 95	90 87	99% 95%	90% 87%	823 756
1	0.002 0.003	99 95	90 86	99% 95%	90% 86%	692 577

Figure 11. The Simulation Results with Different ε_1 and β_2

The optimal distance is 2.6776 that is obtained by the SLF chaotic neural network model with piecewise simulated annealing strategy . Figure 10 shows the optimal path.

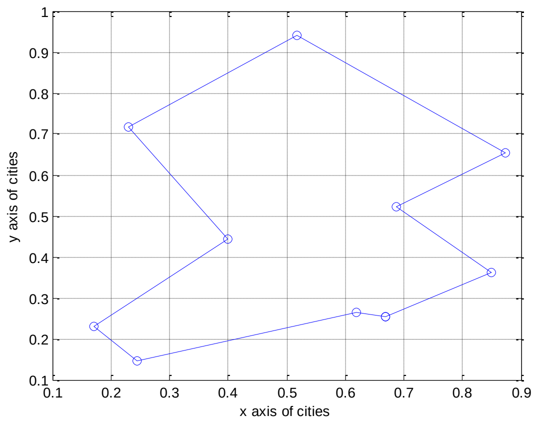

Figure 12. The Optimal Path of 10-city TSP

It can draw the following result s from table II :

(1) In table II, when $\varepsilon_1 = 0$ and $\varepsilon_1 = 1$, the result of model show that the larger annealing parameters, the smaller average number of iterations, which is the foundation we have established the SLF chaotic neural network model with piecewise simulated annealing strategy.

(2) In the table, compare the results with the different β_2 and ε_1, it can be seen that there are obvious reduction in the average number of iterations when the SLF chaotic neural network model with piecewise simulated annealing strategy is used. The larger the value of β_2 and ε_1, the smaller the average number of iterations,

In summary, the piecewise simulated annealing strategy can effectively improve the SLF chaotic neural network search speed. But the model parameter values is crucial, if parameter values are appropriate, it will can greatly improve search ability , on the contrary, the ability to find the optimal solution may cause greatly decreased.

5. Conclusion

This paper studies the effects of combinations of parameters and simulated annealing parameters on SLF chaotic neural network model, thereby, the piecewise simulated annealing strategy is introduced SLF chaotic neural networks model, construct a SLF chaotic neural network model with piecewise simulated annealing strategy. The model is applied to solve function optimization problems and TSP problem, it verify that model obviously improve the convergence rate, meanwhile, it don't loss the optimal solution capabilities.

References

[1] J. J. Hopfield, "Neural networks and physical systems with emergent collectable computational abilities", Proceedings of the National Academy of Sciences, vol. 79, **(1982)**.
[2] J. J. Hopfield, "Neural neurons with graded response have collective computational properties like those of two –state neuron", Proceedings of the National Academy of Sciences, **(1984)**.
[3] K. Aihara, T. Takabe and M. Toyoda, "Chaotic neural Networks", Physics Letters-A, vol. 144, no. 6-7, **(1990)**, pp. 332-340.
[4] L. Chen and K. Aihara, "Chaotic Simulated Annealing by a Neural Network Model with Transient Chaos", Neural Networks, vol. 8, no. 6, **(1995)**, pp. 915-930.
[5] M. Inoue and S. Fukushima, "A Neural Network of Chaotic Oscillators", Progress Theoretical Physics, vol. 87, no. 3, **(1992)**, pp. 771-774.
[6] A. Potapove and M. Kali, "Robust chaos in neural networks", Physics Letters A, vol. 277, no. 6, **(2000)**, pp. 310-322.
[7] J. W. Shua, Z. X. Chen and R. T. Liu, "Self-evolution Neural Model", Physics Letters A, vol. 221, no. 5, **(1996)**, pp. 311-316
[8] X. Y. Qun and Y. X. Ling, "Chaotic neural network with inverse trigonometric functions feedback and its application", Journal of Harbin University of Commerce, vol. 26, no. 3, **(2010)**, pp. 324-328.
[9] X. Y. Qun and S. Ming, "Shannon wavelet chaotic neural network to solve TSP problems", Control Theoryand Applications, vol. 25, no. 3, **(2008)**, pp. 574~577.
[10] H. G. Guang, "Delay feedback control method in chaotic neural networks", Journal of Zhejiang University (Science Edition), vol. 33, no. 1, **(2006)**, pp. 41-43.
[11] X. Y. Qun and H. S. Ping, "Fourier chaotic neural network with application in optimization", Proceedings of the 27th Chinese Control Conference (CCC), **(2008)**.
[12] F. C. Guo, "Self-adapt hybrid chaotic neural network and its application to TSP", Journal of System Simulation, vol. 12, **(2006)**, pp. 3459-3462.
[13] S. ming, "Chaotic neural network and its application based on wavelet and hysteresis", Harbin Engineering University, **(2010)**, pp. 39-45.
[14] X. Y. Qun and S. Ming, "Chaotic neural network and its application", Heilongjiang University Press, **(2012)**.
[15] Y. Y. Gang, "A chaotic neural network with Bessel functions", Journal of Harbin University of Commerce, vol. 29, no. 5, **(2013)**, pp. 561-564.

Author

Yonggang Ye
Male, Born in 1977
Degree: Master

Main research field: Artificial neural network and optimization control.