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On Update Methods of Chaos Neural Network for TSPs

Isao TANAKA†, Yoshifumi NISHIO† and Mikio HASEGAWA‡

† Dept. of Electrical and Electronic Eng.,
Tokushima University
2-1 Minami-Josanjima, Tokushima, Japan
Email: {isao130, nishio}@ee.toushima-u.ac.jp

‡ Wireless Communications Division
Communications Research Laboratory
3-4 Hikarino-Oka, Yokosuka, Japan
Email: mikio@crl.go.jp

Abstract

In this study, we investigate two different update methods of the chaos neural network in order to approach to finding the global minimum solution of TSPs.

By computer simulations for various TSPs, we confirm that the method to change the weights connecting the firing neurons can successfully restrain the regeneration of the once-appeared-solutions.

1. Introduction

Combinatorial optimization problems can be solved with the Hopfield neural network [1]. If we choose connection weights between neurons appropriately according to given problems, we can obtain a good solution by the energy minimization principle. However, the network state is often trapped into a local minimum and do not reach the global minimum. In order to avoid this critical problem, chaos neural networks have been applied to various optimization problems successfully.

Several researchers have also proposed the methods to solve TSPs by using the Hopfield neural networks. However, the Hopfield neural network can find only one solution among numerous possible solutions.

In this study, we try to find the global minimum solutions of TSPs by using neural network. The chaos neural network could find several solutions because of its chaotic dynamical motion. However, the network state visits the once-appeared solution quite often. We investigate three different update methods of the chaos neural network in order to restrain the regeneration of the once-appeared-solutions. By computer simulations for various TSPs, we confirm that the method to change the weights connecting the firing neurons can successfully find many different solutions of TSPs.

2. TSPs and Chaos Neural Network

The TSPs consists of finding the shortest closed path by which every city out of a set of N cities is visited once and only once. For solving N-city TSPs, $N \times N$ neurons are required and the following energy function is define to fire (i,j) neuron at the optimal position:

$$\begin{aligned} E &= \frac{A}{2}\sum_{i=1}^{N}\left(\sum_{j=1}^{N}(x_{i,j}(t)-1)^2\right) \\ &+ \frac{B}{2}\sum_{j=1}^{N}\left(\sum_{i=1}^{N}(x_{i,j}(t)-1)^2\right) \\ &+ \frac{D}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} d_{i,j}x_{i,k}(t)(x_{i,k}(t)+x_{j,k-1}(t)) \end{aligned} \quad (1)$$

The neurons are coupled each other with the synaptic connection weight. Suppose that the weight between (k,l)-th neuron and the (i,j)-th neuron are described by:

$$\begin{aligned} \omega_{i,j,k,l} &= -A\delta_{i,k}(1-\delta_{j,l}) - B\delta_{j,l}(1-\delta_{i,k}) \\ &\quad -Dd_{i,k}(\delta_{l,j+1}+\delta_{l,j-1}) \end{aligned} \quad (2)$$

where A,B and D are positive constant, and $\delta_{r,s}$ is the two-dimentional Kronecker delta, which is defined as

$$\delta_{r,s} = \begin{cases} 1, & \text{if } r = s \\ 0, & \text{if } r \neq s. \end{cases} \quad (3)$$

In order to find different solutions, as many as possible, we apply the chaos neural network to the TSPs.

The equation of the chaos neural network is given as

$$\begin{aligned} x_{i,j}(t+1) &= kx_{i,j}(t) + \sum_{k=1}^{N}\sum_{l=1}^{N}\omega_{i,j,k,l}f(x_{k,l}(t)) \\ &\quad -\alpha f(x_{i,j}(t)) + \theta_{i,j}(1-k) \end{aligned} \quad (4)$$

where $f(x)$ is a sigmoid function

$$f(x) = \frac{1}{1+\exp\left(-\frac{x}{\varepsilon}\right)} \quad (5)$$

and k is time attenuation constant and α controls nonlinearity. Also, we use the method suggested by Sato *et al.* (1.1 in [4]) to decide firing of neurons.

3. Two Proposed Methods

The chaos neural network can find several solutions as it is because of its chaotic dynamical motion. However, the network state visits the once-appeared solution quite often. We propose two different update methods of the chaos neural network in order to restrain the regeneration of the once-appeared-solutions.

3.1. Method 1

In the Method 1, the weights connecting the firing neurons are reduced to restain the regeneration of the firing pattern after every updating. Namely, we choose one of the firing neurons. A constant value "ΔW" is subtracted from the connecting weights from this neuron to the other firing neurons. Moreover, in order to maintain the activity of the network, "$\Delta W/\{N(N+1)\}$" is added to the rest of the weights. This procedure is applied to the all firing neurons.

3.2. Method 2

In the Method 2, the threshold of the firing neurons are reduced to restain the regeneration of the firing pattern after every updating. A constant value "$\Delta\theta$" is subtracted from the thresholds of the all firing neurons. Moreover, in order to maintain the activity of the network, "$\Delta\theta/(N-1)$" is added to the non-firing neurons.

4. Simulated results

Computer simulations of TSPs are performed for the cases of "ulysses16" and "ulysses22" by TSPLIB of a benchmark site. The number of the update of the network state is fixed as 10,000 and the minimum solution of the obtained solutions is evaluated. This trial is iterated 10 times for different initial conditions. and the average of the obtained minimum solutions is "R_{ave}", the shortest is "R_G". The simulated results using the two proposed methods are compared with the results obtained from the normal chaos neural network. Moreover, for character of TSPs, proposed Methods are applied when the obtained solutions is larger than a constant value "P".

The parameter $\alpha = 1.65$(ulysses16), 1.80(ulysses22), $K = 0.3$, $\theta = 3.0$, $A, B = 1.0$, $D = 2.0$ and $\varepsilon = 0.15$.
We carried out computer simulations for various values of the parameters of the ΔW, $\Delta\theta$ and P. The following results are the best we obtained.

Table 2 shows the simulated results for ulysses16.

Table.1 Result of ulysses16 ($\Delta W = 0.0001$ and $\Delta\theta = 0.001$).

	Normal	Method 1	Method 2
R_G	78.15	75.83	75.91
R_{ave}	84.15	80.89	79.57

Next, the simulated results for ulysses22 are shown in Tab. 3.

Table2 Result of ulysses22 ($\Delta W = 0.001$ and $\Delta\theta = 0.0009$).

	Normal	Method 1	Method 2
R_G	95.38	87.14	92.89
R_{ave}	99.16	94.66	98.25

From these tables, we can say that the proposed two methods can find smaller solutions than the ordinary chaos neural networks, especially for the Method1.

And Fig. 1 and 2 show the update of the network state by the case of same initial value.

From these figures, we can say that the proposed two methods can extend to over the update of the network state.

5. Conclusions

In this study, we have tried to find the global minimum solutions of the TSPs by using the chaos neural network. We investigated two different update methods of the chaos neural network in order to restrain the regeneration of the once-appeared-solutions. By computer simulations for various TSPs, we confirm that the method to change the weights connecting the firing neurons can successfully find different smaller solutions of TSPs than the normal chaos neural network.

Finding new methods better than the two methods is our important future research.

References

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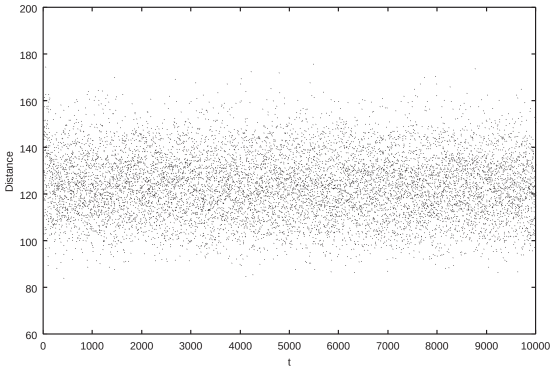
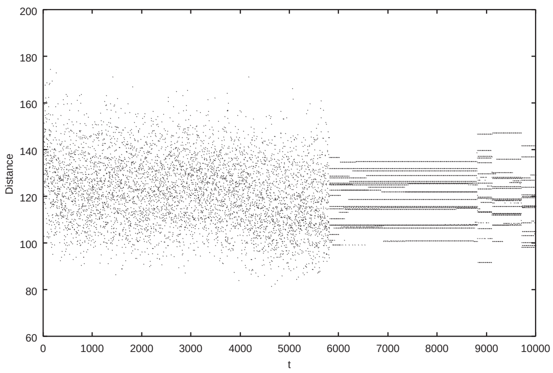
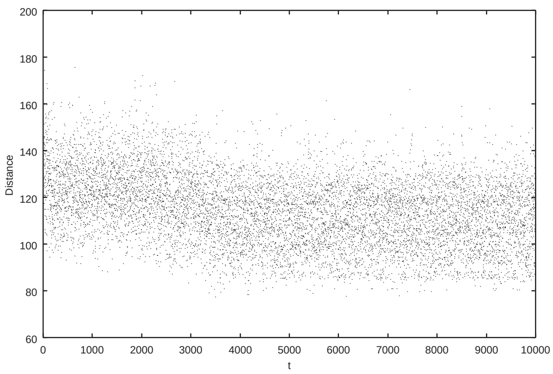


(a) Chaos Neural Network.

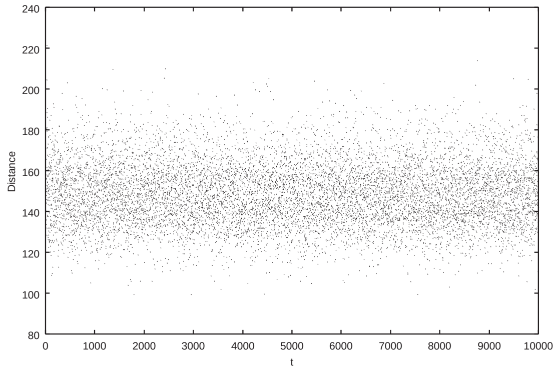


(b) Method 1. $\triangle W = 0.0001$ and $P = 100$.

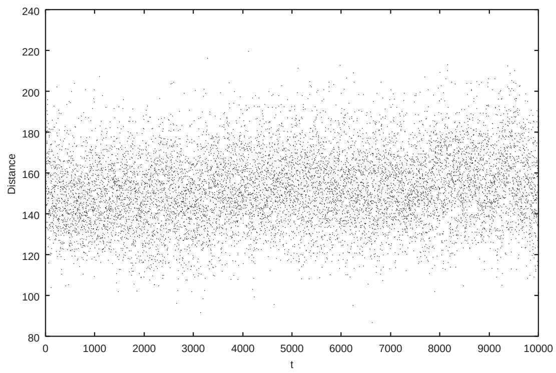


(c) Method 2. $\triangle\theta = 0.001$ and $P = 100$.

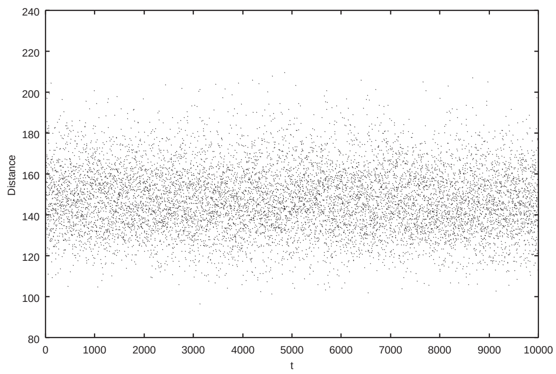
Figure 1: Update of the network state (ulysses16).



(a) Chaos Neural Network.



(b) Method 1. $\triangle W = 0.001$ and $P = 130$.



(c) Method 2. $\triangle\theta = 0.0009$ and $P = 130$.

Figure 2: Update of the network state (ulysses22).