2004 RISP International Workshop on Nonlinear
Circuit and Signal Processing (NCSP'04)
Hawaii, USA, Mar. 5-7, 2004.

Effect of Chaos Noise for Tabu Search Neural Network with 2-Opt for TSPs

Shuichi Aono†, Yoshifumi Nishio† and Mikio Hasegawa*

† Department of Electrical and Electronics Engineering
Tokushima University
2-1 Minami-Josanjima, Tokushima, Japan
Phone:+81-88-656-7470, Fax:+81-88-656-7471
Email: {aoichi, nishio}@ee.tokushima-u.ac.jp

* Communication Research Laboratory

1. Introduction

Although it would be possible to solve combinatorial optimization problems with a huge number of elements, if we have infinite long time, it does not make any sense for practical problems. Realistically, obtaining nearly optimal solutions as quickly as possible is much more important. A technique using the tabu search neural network with 2-opt is very powerful tool to find good solutions within limited time. Moreover, the technique is extended to the neural network with chaotic dynamics to avoid the local minimum problems [1][2].

In this research, we investigate the effect of chaos noise added to the tabu search neural network with 2-opt for TSPs. By carying out computer simulations for various problems, we confirm that the chaos noise has a good effect to avoid local minimum problems and achieves a good performance to find good solutions of the TSPs as well as the tabu search neural network with chaotic dynamincs.

2. Tabu search neural network based on paths [2]

We utilize the 2-opt method for updating solutions of the TSP. As shown in Fig. 1, the 2-opt algorithm interexchanges two paths, $i-a(i)$ and $j-a(j)$, with another two paths, $i-j$ and $a(i)-a(j)$, where $a(i)$ and $a(j)$ are cities next to i and j,respectively. When the 2-opt exchange is done that links the cities i and j, (i,j)th neuron which corresponds to the path between the cities i and j is memorizes in the tabu list.

In the case of solving an n-city TSP, the number of neurons N necessary for the network is n^2 in this approach.

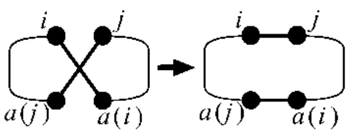

Figure 1: An example of the 2-opt exchange.

In order to realize this tabu search on a neural network, a equations with a synchronous is given as follows:

$$\xi_{ij}(t+1) = \beta(D_o(t) - D_{ij}(t)) \tag{1}$$

$$\zeta_{ij}(t+1) = -\alpha \sum_{d=0}^{s-1} k_r^d x_{ij}(t-d) \tag{2}$$

$$\begin{aligned} x_{ij}(t+1) = \{&\xi_{ij}(t+1) + \zeta_{a(i)a(j)}(t+1) \\ &+ \zeta_{ij}(t+1) + \gamma z_{ij}(t+1)\} \end{aligned} \tag{3}$$

where $D_o(t)$ and $D_{ij}(t)$ are the length of the tour at time t and that with the 2-opt exchange which links cities i and j, β, the scaling parameter of the gain effect, k_r, the decay parameter of the tabu effect, α, the scaling parameter of the tabu effect, $x_{ij}(t)$, the output of the (i,j)th neuron at time t, and $\xi_{ij}(t)$ and $\zeta_{ij}(t)$ are the internal states of the (i,j)th neuron at time t corresponding to the gain effect and the tabu effect of the path between i and j, respectively. And $z_{ij}(t)$ is a chaotic noise to pour in at time t.

If the summation of internal states which expressed Eq. (3), is the largest in all neurons, this (i,j)th neuron fires and the path between cities i and j is connected by the 2-opt exchange. For memorizing the connection of this path, $x_{ij}(t+1)$ is set to 1, and the outputs of all other neurons $x_{kl}(t+1)$, $(k,l) \neq (i,j)$ and $(k,l) \neq (a(i),a(j))$ are set to 0.

3. Chaos noise

In this research, we use as a noise the time series of the chaos generated by the logistic map of the following equation:

$$z_{ij}(t+1) = r z_{ij}(t)(1 - z_{ij}(t)). \tag{4}$$

The chaotic sequence is normalized by

$$\hat{z}_{ij}(t+1) = \frac{z_{ij}(t) - \bar{z}}{\sigma_z} \tag{5}$$

where. $\bar{z}$ is the average of $z_{ij}(t)$ and σ_z is the standard deviation of $z_{ij}(t)$. In this research we use intermittent chaos near the three-periodic window obtained from the logistic map with $r = 3.828$. The time series of the intermittent chaos noise near the three-periodic window to be used is shown in Fig. 2.

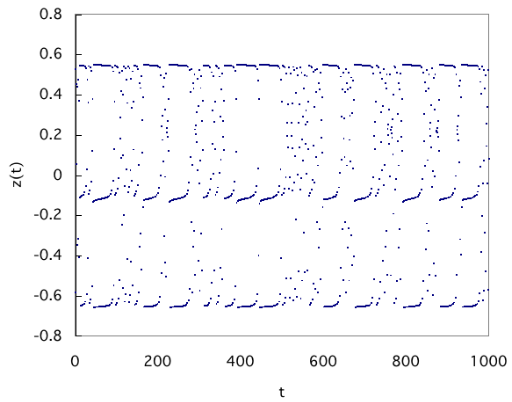

Figure 2: Intermittent chaos noise near the three-periodic window.

4. Chaotic neural network based on paths [2]

For the comparison we consider the technique extended to the neural network with chaotic dynamics. This technique is almost the same as the tabu effect of the exponential tabu search realized by the tabu search neural network described above. However, there is a significant difference on the output function. The output of each neuron $x_{ij}(t)$ of the above tabu search neural network is determined to be 0 or 1 by detecting the maximum internal state of Eq. (3) among all neurons. On the other hand, the chaotic neural network originally adopts an analog sigmoidal function.

Then, this method, which includes both of the tabu effect and chaotic dynamics, is realized by the following equations with an asynchronous updating:

$$\xi_{ij}(t+1) = \beta(D_o(t) - D_{ij}(t)) \tag{6}$$

$$\eta_{ij}(t+1) = -W \sum_{k=1}^{n} \sum_{l=k+1}^{n} x_{kl}(t) + W \tag{7}$$

$$\zeta_{ij}(t+1) = -\alpha \sum_{d=0}^{s-1} k_r^d \{x_{ij}(t-d)\} + \theta \tag{8}$$

$$\begin{aligned} x_{ij}(t+1) = f\{&\xi_{ij}(t+1) + \eta_{ij}(t+1) \\ &+ \zeta_{a(i)a(j)}(t+1) + \zeta_{ij}(t+1)\} \end{aligned} \tag{9}$$

If $x_{ij}(t+1) > 1/2$, the (i, j)th neuron fires and the path between cities i and j is connected with the 2-opt exchange as shown in Fig. 1.

For numerical calculation, Eq. (8) can be reduced to the following forms: if $t < s$,

$$\zeta_{ij}(t+1) = k_r \zeta_{ij}(t) - \alpha x_{ij}(t) + R \tag{10}$$

otherwise $(t \geq s)$,

$$\zeta_{ij}(t+1) = k_r \zeta_{ij}(t) - \alpha x_{ij}(t) + R + \alpha k_r^s x_{ij}(t-s) \tag{11}$$

where $R = \theta(1 - k_r)$. Here, we assume that $x_{ij}(u) = 0$ for $u < 0$, which means that there is generally no tabu effect for initial conditions.

5. Simulated results

In this research, we use three problems, "bays29", "rd100" and "lin105" from TSPLIB [3]. The results are summarized in Table 1. And convergence of the solution to "lin105" is shown in Figs. 3 and 4. Figure 3 shows that the convergence of the solution of the tabu search and the tabu search with chaos noise. Figure 4 shows that the convergence of the solution of the tabu search with chaos noise and the chaotic search. Here, parameter values are fixed as $\beta = 75.0$, $k_r = 0.99$, $R = 0.05$, $W = 0.15$, $\epsilon = 0.002$, and $\gamma = 0.07$. Moreover, the number of iterations is 10,000.

Table 1: The results of the tabu search (TS), the tabu search with chaos noise (TS-C) and the chaotic search (CS).

Problem	Optimal Solution	TS	TS-C	CS
bays29	9074	9074	9074	9074
rd100	7910	7955.0	7950.2	7940.6
lin105	14379	14500.4	14436.3	14391.7

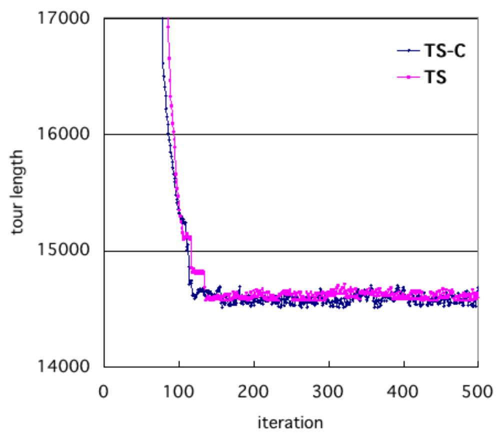

Figure 3: Convergence of the solution of the tabu search (TS) and the tabu search with chaos noise (TS-C).

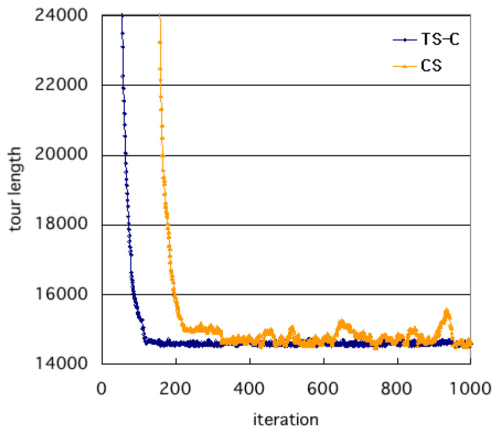

Figure 4: Convergence of the solution of the tabu search with chaos noise (TS-C) and the chaotic search (CS).

Table 1 shows that the tabu search with chaos noise exhibits much better performance than the tabu search. Although the chaotic search can find the solutions closer to the optimal solution than the tabu search with chaos noise, there are many parameters to be tuned in the chaotic search. Moreover, the chaotic search applied an asynchronous updating, so that the convergence speed of the tabu search with chaos noise is faster than the chaotic search from Fig. 4.

6. Conclusion

In this research, we have investigated the effect of the chaos noise added to the tabu search neural network with 2-opt for TSPs. By carying out computer simulations for various problems, we confirmed that the chaos noise has a good effect to avoid local minimum problems and achieves a good performance to find good solutions of the TSPs as well as the tabu search neural network with chaotic dynamincs.

As a future subject, we investigate the effect to add different noises to the network.

Acknowledgement

This work was partly supported by Kayamori Foundation of Informational Science Advancement's Research Grant.

References

[1] Hasegawa, M., Ikeguchi, T., Aihara, K., "Combination of Chaotic Neurodynamics with the 2-opt Algorithm to Solve Traveling Salesman Problems", Physical Review Letters, Vol. 79, pp. 2344-2347, 1997.

[2] Hasegawa, M., Ikeguchi, T., Aihara, K., "Solving large scale traveling salesman problems by chaotic neurodynamics", Neural Networks, 15, pp. 271-283, 2002.

[3] "TSPLIB", http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/