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Hopfield Neural Network with Glial Network

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Abstract

A glia is a nervous cell existing in a brain. This cell has important functions for the higher brain function. We have proposed a glial network for an artificial network from functions of the biological glia. In this study, we propose a Hopfield Neural Network (Hopfield NN) with glial network. In the Hopfield NN with glial network, we connect the glias with the neurons one by one. The glia generates a pulse when the glia is excited by the output of the connecting neuron. This pulse affects neuron's threshold and neighboring glias. By solving Traveling Salesman Problem, we confirm that the proposed Hopfield NN has a better performance than the conventional Hopfield NN.

1. Introduction

Neural networks have been investigated by many researchers, because the neuron composes the brain. The glia is one of nervous cells existing in the brain. For a long time, functions of this cell had been regarded as the support cell of the neuron. However, some researchers found its new functions [1]. It can transmit signals by the ions concentration wave and affect neurons [2][3]. Currently, this cell is considered to important cell for the brain functions. In the previous study, we proposed some artificial network models of the glia [4][5]. We added the glia network models to Multi-Layer Perceptron (MLP). In this model, the glias generate pulses when the glias are excited by a stimulus of connecting neurons. The pulse propagates to the connecting neurons and the neighboring glias. We showed that the learning performance of the MLP and some abilities are improved by the glia network model. The glial network is one dimension structure.

In this study, we extend the glial network to two dimension structure. We propose the Hopfield Neural Network (Hopfield NN) with glial network. The conventional Hopfield NN is proposed by J.J. Hopfield in 1982 [6]. An energy function is decreased by using the steepest descent method. It can be applied to an associative memory, Travel Salesman Problem (TSP), and so on. The Hopfield NN is trapped into a local minimum. We often add a noise to the Hopfield NN for escaping from the local minimum [7][8]. We added the glial network to the Hopfield NN. In the Hopfield NN with glial network, the glias are arranged in a grid-like formation. The glias are connected with the neurons one by one. When the glia is excited, the glia generates the pulse. After that, the pulse propagates to neighboring glias. We show that the performance of the proposed Hopfield NN by solving the TSP. Moreover, we confirm that the proposed Hopfield NN has a better performance than the conventional Hopfield NN.

2. Hopfield NN with Glial Network

The Hopfield NN was proposed by J.J. Hopfield. This network has complete and symmetric connections which is shown in Fig. 1. (a) is an example of connections of Hopfield NN. In this study, neurons are arranged in the grid-like formation (b). If we give any constraint conditions to the Hopfield NN, the Hopfield NN can decrease the energy. Thus, the Hopfield NN is applied to solve the optimization problem. However, the Hopfield NN has the local minimum problem. Because this network uses the steepest descent method. This method can decrease the energy, however, the solution is often trapped into a local minimum.

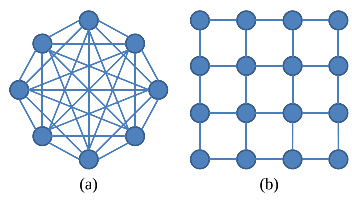


Figure 1: The Hopfield NN.

2.1. Hopfield NN for Solving TSP

The TSP is a famous optimization problem. This task has $N \times N$ cities in the two dimensional structure. We should visit all cities, then, we can not visit same city. We want to find the shortest tour. The Hopfield NN is known to be able to solve the TSP. We can obtain the weight parameters from the constraint conditions. If we solve TSP by using the Hopfield NN, the energy function is obtained by Eq. (1).

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

where E is an energy function, x is an output of the neuron, d is distance between the city and the city, and A, B and D are constant number. We can obtain the weight of connections for solving the TSP from the energy function. The weight of connections is calculated by Eq. (2).

$$w_{ijmn} = -A\delta_{im}(1-\delta_{jn}) - B\delta_{j}n(1-\delta_{im}) - Dd_{im}(\delta_{n,j+1}+\delta_{n,j-1}), \quad (2)$$

$$h_{ij} = A + B, \quad (3)$$

where w is the weight of connections of neurons, δ is Kronecker 's delta and h is a threshold of the neuron.

2.2. Neuron Updating Rule

In this study, we propose the Hopfield NN with glial network shown in Fig. 2. The glial network is inspired from the feature of the biological glia. The glia is the nervous cell existing in the brain. This cell transmits signals to the glias and the neurons by ions concentration. We consider that the glia affect good influence to the artificial neural network. In the proposed method, the glias are connected with the neurons one by one. The excited glias generate the pulse and affect the connecting neurons' thresholds. Moreover, the pulse propagates to the neighboring glias. We consider that the pulses give the energy to the Hopfield NN, and that the Hopfield NN escapes out from the local minimum.

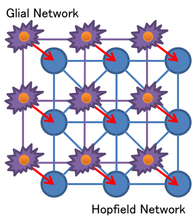


Figure 2: The Hopfield NN with glial network.

The neurons connect with all other neurons in the Hopfield NN. The neuron updating rule is described by Eq. (4).

$$u_{i,j}(t+1) = \sum_{m=1,n=1}^{N} w_{ij,mn}x_{mn}(t) + h_{ij}, \quad (4)$$

where u is an internal state of neuron, and x is an output or input of neurons. w is decided by Eq. (2). Thus, the w is not changed during a simulation. When we give the initial value to the neurons, the neurons update by themselves.

The proposed neuron updating rule is defined by Eq. (5)

$$u_{i,j}(t+1) = \sum_{m=1,n=1}^{N} w_{ij,mn}x_{mn}(t) + h_{ij} + \phi(t), \quad (5)$$

where *phi* is a glial pulse. In Eq. (5), we give the glias' pulses ϕ to the neurons' thresholds. The glias support the Hopfield NN for escaping from the local minimum. The sigmoid is used for an activating function. It is described by Eq. (6).

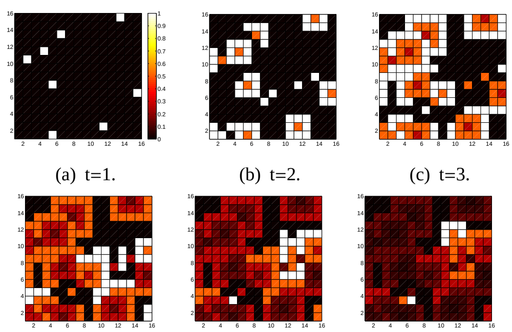
$$x_{ij}(t+1) = \frac{1}{1+e^{-u_{ij}(t+1)}}. \quad (6)$$

2.3. Glial Network

The glia has relationships with neighboring glias and the connecting neurons. If the neuron has a large output, the connected glia is excited. We choose some neurons which have large output in the network. The number of neurons to be chosen is K. In one simulation, K is not changed. The glia has a period of inactivity (T) when the glia generate the pulse.. During this period, the glia can not excite. When the glia is excited by the connecting neuron, the glia generate a pulse. This pulse propagates to the threshold of the connecting neurons and the neighboring glias. The glial network has a propagation range of the pulse (R). If R is 2, the glial effect influence the states of the glias in two neighborhoods. We define the output of the glia in Eq. (7).

$$\phi(t+1) = \beta\phi(t), \quad (7)$$

where β is an attenuated parameter. We use β between 0 and 1. Figure 3 is an example of the generation pulses. We use the 16×16 glias, $K = 8$ and $R = 2$. First, the excitation glias generate the pulses at some positions. Second, the neighboring glias of first excitation glias are excited. At $t = 3$, we can see that the pulses are generated like square.



(a) t=1. (b) t=2. (c) t=3.

(d) t=4. (e) t=5. (f) t=6.

Figure 3: Pulse propagation.

3. Simulation Results

In this section, we show the simulation results of the Hopfield NNs. We use the three different TSPs (ulysses16, att48 and gr96). We compare three Hopfield NNs which are the conventional Hopfield NN, the Hopfield NN with random noise and the Hopfield NN with glial network. The Hopfield NN with random noise is given uniformed random noise to every neuron's threshold. We use four kinds of measures to be obtained by 100 trials for the evaluation of the performance. They are an average distance (Ave.), a minimum distance (Min.), a maximum distance (Max.) and a standard deviation (Std. Dev.). We show a ratio of the results of the proposed Hopfield NN to the results of the conventional Hopfield NN.

3.1. Ulysees16

First, we show the results of ulysses16 in Table 1. The Hopfield NN with random noise is the best of all in the average of distance. However, the Hopfield NN with glial network and the Hopfield NN with random noise obtain the optimal solution. The conventional Hopfield NN is the worst of all. We consider that the conventional Hopfield NN is trapped into the local minimum. From this result, the Hopfield NN with glial network can escape from the local minimum. Figure 4 shows that we obtained each local optimum solution from three Hopfield NNs.

Table 1: Statistic results as ulysses16.

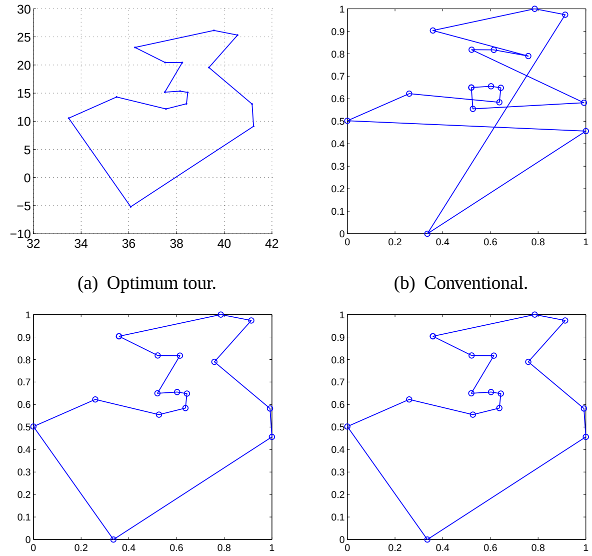
	Ave.	Min.	Max.	Std. Dev.
Random	0.7505	0.8052	0.7859	0.4648
Glia	0.7805	0.8052	0.8131	0.5425

3.2. Att48

Next, we show the results of att48. Table 2 is the statistic results. In this table, the tendency in the measures is similar to ulysses16. We consider that the Hopfield NN with glial network has high ability of searching local optimal solution. In this case, the Hopfield NN with glial network obtains the best tours of all. However, all Hopfield NN cannot obtain the optimal solution. In this case, the Hopfield NN with glial network obtains the best tours of all. Figure 5 shows that we obtained each local optimum solution from three Hopfield NNs.

Table 2: Statistic results as att48.

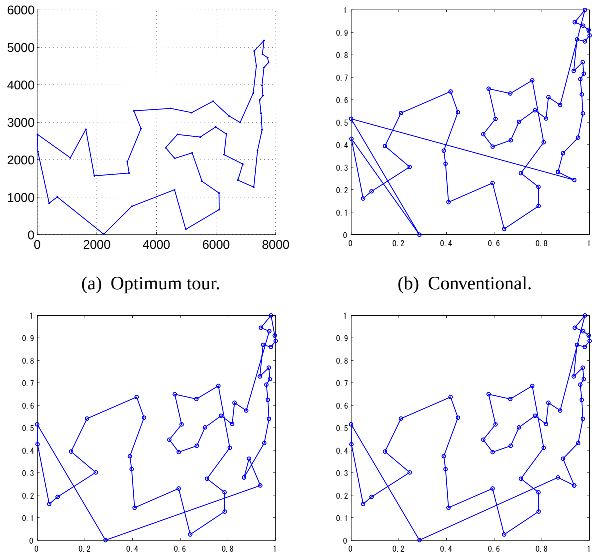
	Ave.	Min.	Max.	Std. Dev.
Random	0.8388	0.9036	0.9162	0.7259
Glia	0.9219	0.8883	1.1555	3.2800



(a) Optimum tour. (b) Conventional.

(c) Random. (d) Glial network.

Figure 4: Ulysses16.



(a) Optimum tour. (b) Conventional.

(c) Random. (d) Glial network.

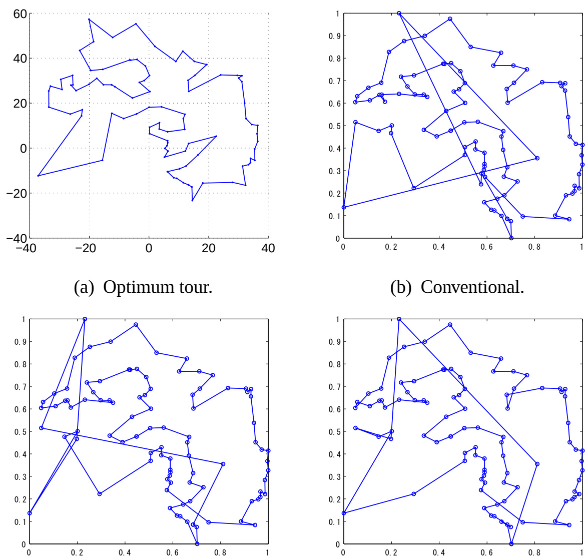
Figure 5: Att48.

3.3. Gr96

Finally, we show the results of solving gr96. Table 3 is the statistic results. In the average of distance , the Hopfeild NN with random noise is better than the proposed Hopfield NN. We consider that the Hopfield NN with random noise can search local optimum solution over wider range than the proposed Hopfield NN. Because in the Hopfield NN with random noise, the random noise is inputted to every neuron. In the proposed Hopfield NN, the glial effects are locally. Thus, the proposed Hopfield NN cannot decrease the network energy than the Hopfield NN with random noise. However, the minimum distance of the Hopfield NN with glial network is the shortest of all. From this result, we consider that the proposed Hopfield NN has the high local search performance. Figure 6 shows that we obtained each local optimum solution from three Hopfield NNs.

Table 3: Statistic results as gr96

	Ave.	Min.	Max.	Std. Dev.
Random	0.9428	0.9842	0.9038	1.0821
Glia	0.9767	0.9508	1.0192	0.9105



(a) Optimum tour. (b) Conventional. (c) Random. (d) Glial network.

Figure 6: Gr96.

4. Conclusion

In this study, we have proposed the Hopfield NN with glial network which is inspired from the functions of the biological glia. We added the glial network to the Hopfield NN. The excited glia generates a pulse, this pulse affect neuron's threshold and neighboring glias. The glial network give the energy to the Hopfield NN for escaping from local minimum. From solving the TSP, we confirm that the proposed Hopfield NN is better performance than the conventional Hopfield NN. In all simulations, the Hopfiled NN with glial network has the best tours. However, the average of distance of proposed Hopfield NN is worse than the Hopfield NN with random noise. From these results, the proposed Hopfield NN has high local searching ability. We consider that the glial network gives the local energy to the Hopfield NN. In the future works, we will confirm that the glial effect is how to influence the Hopfield NN. Moreover, we will find the effective parameters of the glial network for solving the TSP.

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