2010 International Workshop on Nonlinear Circuits, Communication and Signal Processing
NCSP'10, Waikiki, Hawaii, March 3-5, 2010

Parameter Dependency of Chaos Glial Network Connected to Multi-Layer Perceptron

Chihiro Ikuta†, Yoko Uwate‡ and Yoshifumi Nishio†

†Tokushima University
2-1 Minami-Josanjima, Tokushima, Japan
Phone:+81-88-656-7470
Email: { ikuta, nishio} @ee.tokushima-u.ac.jp

‡University / ETH Zurich
Winterthurerstrasse 190, CH-8057 Zurich, Switzerland
Email: yu001@ini.phys.ethz.ch

Abstract

We proposed chaos glial network connected to Multi-Layer Perceptron (MLP). The glial network is inspired by astrocyte which is glial cell in the brain. Glial cell generates chaotic oscillation and this oscillation is propagated other glial cells into the glial network. We consider that this oscillation gives good influence to MLP learning.

In this paper, we investigate chaos glial network connected to MLP in some conditions. We apply the MLP networks for solving Two-Spiral Problem (TSP). TSP is a problem which classifies two spirals drawn on the plane, and it is famous as the high nonlinear problem. By computer simulations for solving TSP, we confirm that chaos glial network connected to MLP has strong dependency for glial network parameters.

1. Introduction

Back Propagation (BP) was introduced by Rumelhart in 1986 [1]. BP is used for learning algorithm of Multi-Layer Perceptron (MLP) and the error propagates backwards in the network. MLP using BP algorithm is well known to perform for the pattern classification tasks. However, the solution of the network often falls into the local minimum, because BP uses the steepest descent method for the leaning process. Generally, if the solution of MLP falls into the local minimum, it can not escape. In order to avoid this problem, some methods to release the solution from the local minimum are required.

Recently, the mechanism of astrocyte becomes clear with the advances in neuroscience technology. Astrocyte is a glial cell which existing in a central nervous system of brain. Several research groups discovered that astrocytes affect to neurons with signal [2]. We proposed a chaos glial network connected that to MLP and we confirmed this MLP network was better performance than conventional MLP [3]. In the glial network, glial cell connected to neighborhood glial cells and influence of glial cell propagates. We showed that this network gave good influence to MLP learning.

In this study, we investigate chaos glial network connected to MLP in some conditions. We clearly discuss parametric dependency of chaos glial network connected to MLP. We apply the MLP to the TSP [4] and confirm the efficiency by computer simulations.

2. Multi-Layer Perceptron

MLP is the most famous feed forward neural network. This network is used for pattern recognition, pattern classification, and other tasks. MLP has some layers, it has mainly input layer, hidden layer, and output layer. Generally, it is known that MLP can solve a more difficult task if the number of layer or neuron is increased. We consider MLP which is composed of four layers (one input layer, two hidden layers and one output layer), and MLP has the glial network in the second layer of the hidden layer. The proposed glial network connected to MLP structure (connected 2-20-40-1) is shown in Fig. 1.

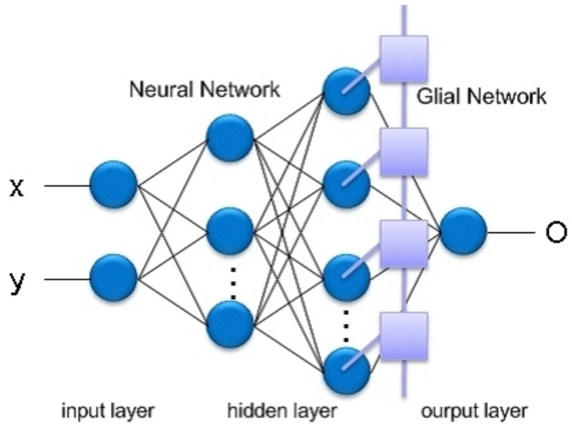

Figure 1: Chaos glial network connected to MLP.

2.1. Neuron Updating Rule

The updating rule of neurons in the input layer, the first hidden layer and the output layer is described by Eq. (1) which is conventional updating rule.

$$x_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t)\right) \quad (1)$$

In the chaos glial network connected to MLP, chaotic oscillation is added to neurons in the second hidden layer. This neuron's updating rule is following as Eq. (2).

$$x_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t) + \alpha\Psi_i(t)\right), \quad (2)$$

where x : input or output, w : weight parameter, θ : threshold, ψ, Ψ : random oscillation, α : amplitude of random noise and f : output function. And we use sigmoid for the output function as Eq. (3).

$$f(a) = \frac{1}{1+e^{-a}} \quad (3)$$

In the biological neural network, it is known that the glial cells affect to the neighbor neurons over a wide range by propagating in the network [5]. In order to realize phenomena, we add chaotic oscillation to neurons by using Eq. (4). In this simulation, we use skew tent map which is given Eq. (5).

$$\Psi_i(t) = \sum_{k=-m}^{m} \beta^{|k|}\psi_{i+k}(t-k), \quad (4)$$

$$\psi_i(t+1) = \begin{cases} \frac{2\psi(t)+1-A}{1+A} & (-1 \le \psi(t) \le A) \\ \frac{-2\psi(t)+1+A}{1-A} & (A < \psi(t) \le 1) \end{cases}, \quad (5)$$

where β denotes attenuation parameter and k is the propagating range in the glial network. Chaotic oscillation is propagating in the glial network as shown in Fig. 2 and it takes time depending on distance. For example, when the glial cell is located three units far from certain neuron, effect of chaotic oscillation arrives to the neuron after three learning steps. And chaotic oscillation decreases while chaos is propagating in the network.

2.2. Back Propagation

The error of MLP propagates backward in the feed forward neural network. BP algorithm changes value of weights to obtain smaller error than before. The error of the network is given by Eq. (6).

$$E = \frac{1}{2}\sum_{i=1}^{n}(t_i - O_i)^2, \quad (6)$$

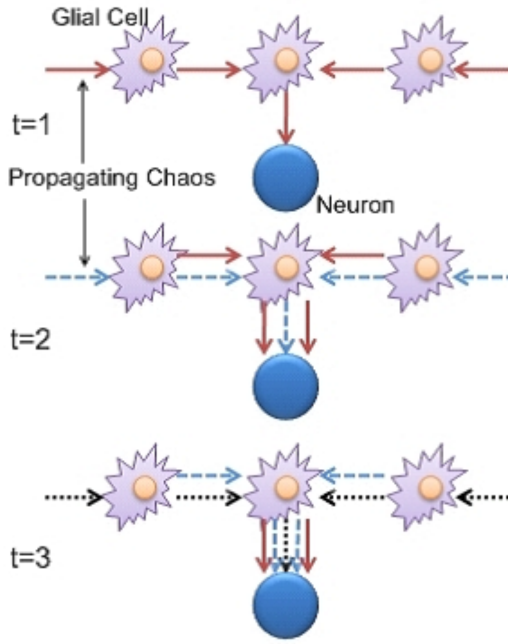

Figure 2: Propagating chaotic oscillation in the network.

where E: error value, t: target value and O: neuron output. By changing the value of weights, MLP's error becomes smaller. Therefore, partial differential of the weight is carried out by Eq. (7).

$$\Delta W_{kj} = -\eta\frac{\partial E}{\partial w_{kj}} \quad (7)$$

3. Simulations

In this section, the difference in the performance of our MLP; We investigate behavior of MLP as changing glial network's parameters.

3.1. Two-Spiral Problem

We apply the proposed network for solving TSP [4]. MLP learns to each point of two spirals, and MLP learns by using the standard BP algorithm. In this simulation, we use 98 points of two spiral for learning.

3.2. Simulation Results

Each MLP learns the two spirals by setting up same weights before learning process. We prepare 98 data of two spirals as shown in Fig. 3. The number of learning points is fixed as 500000. We investigate the error which is modified in the meantime. The error function is defined as Eq. (8).

$$E = \frac{1}{n}\sum_{i=1}^{n}|t_i - O_i| \quad (8)$$

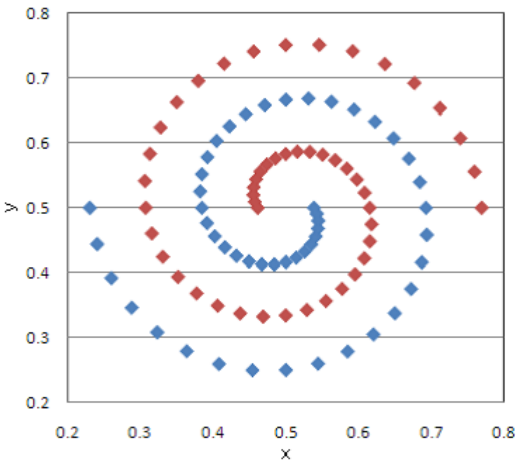

Figure 3: Two-spiral problem.

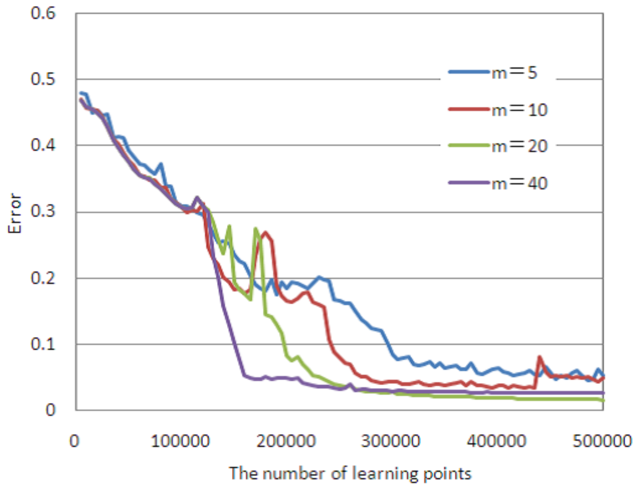

Figure 4: Error curve by MLP network as changing m.

3.2.1. *m Dependency*

We prepare 98 data of two spirals. The number of learning points is fixed as 500000. We change the propagating range m (5, 10, 20 and 40) in the Eq. (4) and we use $\beta = 0.8$. Table 1 shows simulation result of each MLP learn to 98 points.

Table 1: Performance of MLP with chaos glial network by changing propagating range of chaotic oscillations.

Points	5	10	20	40
100000	0.318	0.318	0.299	0.299
200000	0.194	0.230	0.197	0.200
250000	0.152	0.182	0.149	0.153
300000	0.103	0.129	0.084	0.097
350000	0.092	0.108	0.065	0.073
400000	0.078	0.085	0.050	0.069
450000	0.075	0.075	0.043	0.044
500000	0.068	0.077	0.035	0.036

From this table, when the propagating range is fixed as m=20, 40, MLP gains better performance than the case of m=5, 10. We consider that propagating oscillation is becoming small by β in the far glial cell.

Figure 4 is typical result as using each m. In this result, MLP learning curve converged earlier as propagating oscillations are more wide range.

3.2.2. *β Dependency*

In this simulation, we use $m = 20$ from before simulation result. The number of learning points is fixed as 500000. Table 2 shows result of each MLP as changing β (0.2, 0.4, 0.6, 0.8 and 1.0).

Table 2: Performance of MLP with chaos glial network by changing attenuation parameter.

Points	0.2	0.4	0.6	0.8	1.0
100000	0.309	0.291	0.307	0.299	0.396
200000	0.220	0.198	0.206	0.197	0.301
250000	0.164	0.136	0.160	0.149	0.258
300000	0.133	0.114	0.112	0.084	0.229
350000	0.104	0.087	0.090	0.065	0.231
400000	0.077	0.078	0.073	0.050	0.195
450000	0.064	0.072	0.066	0.043	0.188
500000	0.060	0.062	0.053	0.035	0.179

We can see that MLP obtains the best result when the attenuation parameter is set to $\beta = 0.8$. While, in the case of $\beta = 1.0$, MLP shows the worst result. Moreover, the results become better by increasing the value of β expect $\beta = 1.0$. We consider that influences of other glial cells are important for MLP learning.

Figure 5 is typical result of changing the attenuation parameter. The learning curve of $\beta = 1.0$ is very vibrating because chaotic oscillation is too large.

3.2.3. *η Dependency*

We showed this MLP network gives the best result to use $m = 20$ and $\beta = 0.8$. In this section, we investigate learning coefficient dependency of our MLP. We use different learning

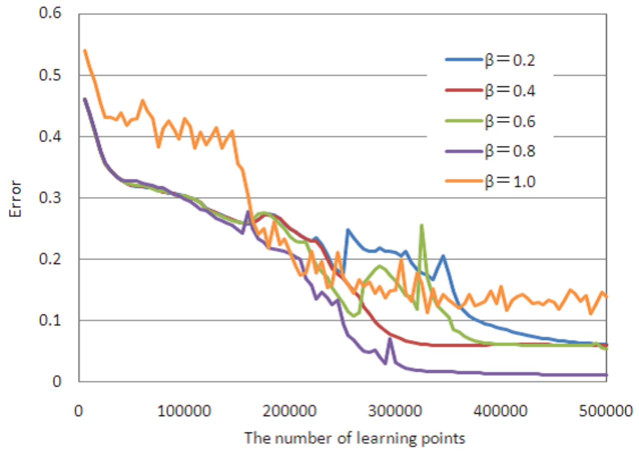

Figure 5: Error curve by MLP networks as changing β.

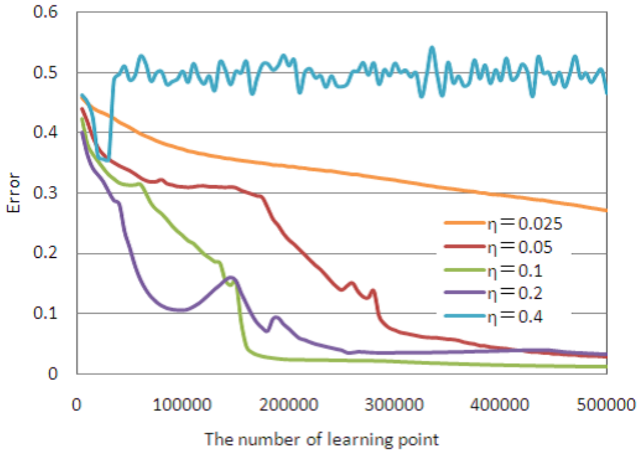

Figure 6: Error curve by MLP networks as changing η.

coefficient (η = 0.025, 0.05, 0.1, 0.2, 0.4). From this table,

Table 3: Performance of MLP with chaos glial network by changing learning coefficient.

Points	0.025	0.05	0.10	0.20	0.40
100000	0.396	0.299	0.158	0.146	0.477
200000	0.351	0.197	0.071	0.148	0.498
250000	0.342	0.149	0.051	0.222	0.489
300000	0.329	0.084	0.048	0.198	0.495
350000	0.321	0.065	0.037	0.215	0.508
400000	0.314	0.050	0.064	0.234	0.492
450000	0.309	0.043	0.082	0.234	0.495
500000	0.303	0.035	0.089	0.233	0.494

we confirm that the error of MLP can converge fast when the learning coefficient is set to the large value. However, if the parameter of the learning coefficient is too large such as η = 0.2, 0.4, MLP hardly learn to the two-spiral. When the learning coefficient is very small (η = 0.025), MLP could not finish learning at 500000 times.

Figure 6 shows one example of the error curve as changing η. When the learning coefficient is fixed as η = 0.4, the error curve vibrates and MLP could not learn the two-spiral. In the case of η = 0.05, 0.1, 0.2, the learning curves are very smooth and when learning coefficient is large, convergence of error is fast.

4. Conclusions

In our study, we have investigated parameter dependency of chaos glial network connected to MLP. This network gave chaotic oscillations to the second hidden layer's neuron. We confirmed that chaos glial network connected to MLP had strong dependency for glial network parameter.

References

[1] D.E. Rumelhart, G.E. Hinton and R.J. Williams, "Learning Representations by Back-Propagating Errors," *Nature*, vol.323-9, pp.533-536, 1986.

[2] P.G. Haydon, "Glia: Listening and Talking to the Synapse," *Nature Reviews Neuroscience*, vol. 2, pp.844-847, 2001.

[3] C. Ikuta, Y. Uwate and Y. Nishio, "Chaos Glial Network Connected to Multi-Layer Perceptron for Solving Two-Spiral Problem," *Proc. ISCAS'10*, May 2010. (Accepted)

[4] J.R. Alvarez-Sanchez, "Injecting knowledge into the Solution of the Two-Spiral Problem," *Neural Computing & Applications*, vol.8, pp.265-272, 1999.

[5] S. Koizumi, M. Tsuda, Y. Shigemoto-Nogami and K. Inoue, "Dynamic Inhibition of Excitatory Synaptic Transmission by Astrocyte-Derived ATP in Hippocampal Cultures," *Proc. National Academy of Science of the U. S. A*, vol.100, pp.11028-11028, 2003.