Investigation of Glia-Neuron Network with Group Learning of Hidden-Layer Neurons

Chihiro Ikuta[†], Yoko Uwate[†], Yoshifumi Nisho[†], and Guoan Yang[‡]

[†]Dept. of Electrical and Electronic Eng., Tokushima University, 2-1 Minami-Josanjima, Tokushima Japan
Email: {ikuta, uwate, nishio}@ee.tokushima-u.ac.jp
[‡]Dept. of Automation Science and Technology, School of Electronic and Information Eng.,
Xi'an Jiaotong University, No. 28 Xianning West Road, Xi'an City, Shaanxi Province, China
Email: gayang@mail.xjtu.deu.cn

abstract

A glia is an important cell for a higher brain function. This cell can transmit signals to neurons and glias by using ion concentrations. From this feature, we propose a glia-neuron network with group learning of hidden-layer neurons. In this model, the neurons in a hidden-layer are separated to some groups. We connect glias to each group. These neurons are switched between a learning term and a non-learning term according to firing of the glias. The time length of learning term is controlled by the glia firing. The glia firing depends on the integration of the connecting neuron outputs. Thus, the neurons and the glias are correlated to each other. By simulations, we confirm that the performance and characteristics of the proposed model.

1. Introduction

The glia is an important nervous cell for a higher brain function. However, this cell had not been investigated about detail, because this cell was considered to a support cell of a neuron. Recently, some researchers discovered novel glial functions [1]-[3]. The glia uses an ion concentration to a transporter of signals. The ions are a Ca^{2+}, a glutamate acid, an adenosine triphosphate, and so on [4][5]. Among them, we notice the Ca^{2+}. The glia release the Ca^{2+} when glia is received stimulus from the neurons [6]. Moreover, the Ca^{2+} transmits to wide range in the brain and composes the brain function.

N. Takatas reported that the Ca^{2+} affects the synaptic Long-Term Potentiation (LTP) by an experiment on living animals [7]. In that research, they used two mice. One mouse has normal glia. On the other hand, the mouse has the additional genetic defect glia which cannot become detached to Ca^{2+}. In the genetic defect mouse, they could not observe the LTP. In the normal mouse, they could observe the LTP by the increase of the response. Moreover, the increase of the D-serine was observed in the increase of the Ca^{2+} concentration. The D-serine is the important ion for LTP. Thereby, we can say that the glia corresponds to the LTP of the synapse.

In this study, we propose a glia-neuron network with group learning of hidden-layer neurons. The glia closely relate to the neuron works in the biological system. The proposed model is inspired from relationships between the glias and the neurons. In this model, we connect the glias to the neurons in the hidden-layer. These neurons are separated to some groups. The groups are switched between a learning term and non-learning term according to firing of the glia. The glias receive the output of connecting neurons in the same group and integrate the outputs of neurons with respect to the time. Firing time length of the glia is decided by amount of the integrated outputs. The glia does not have a learning method, however the neurons are learned by Back Propagation (BP) algorithm [8]. Thus, the responses of glias are dynamically changed during the iterations. We consider that the artificial neural network is improved by the relationships between the neuron and the glia. By the computer simulations, we confirm that the performance and characteristics of the proposed network.

2. Proposed method

The Multi-Layer Perceptron (MLP) is a famous feed forward neural network. It is applied to various nonlinear task such as an approximation of function, a classification task, a data mining, and so on. In general, the MLP is learned by BP algorithm [8] which uses the steepest decent method. However, the BP algorithm often falls into local minima. We give the noise to the MLP for escaping out from the local minimum. The noise is efficient to difficult tasks, because a difficult task has many local minima. However, the noise encumbers the learning when the MLP solves the easy task. In previous study, we proposed the glia-neuron network model [9]. The neurons in the hidden-layer have a switching between the learning and non-learning term. The learning term and non-learning term are periodically switched. We confirmed that the switching of two terms improves the MLP learning performance. However, the learning of this network is converged earlier, because the parameters are fixed.

In this study, we propose the glia-neuron network with group learning of hidden-layer neurons. The construction of the proposed network is presented in Fig. 1. In this model, we connect glias with the neurons in the hidden-layer. They influence each other during the iterations. The neurons are separated to some groups. Each group is switched between the learning term and non-learning term according to firing of the connected glia. Firing of the glias periodically change. In this model, each glia has different time length of the firing. The time length of firing is decided by the connecting neuron outputs. The glia integrates the neurons' outputs in the connecting group with respect to iterations. The time length of learning term is decided by Eq. (1).

$$L_g = \frac{L_{max}}{TN} \sum_{t=1}^{T} \sum_{n=1}^{N} O_{gnt}, \qquad (1)$$

where L is a time length of learning term, g is a group number, T is a iteration length from a start time of learning term of first group and the end time of learning term of last group, N is the number of neurons in the same group, and O is an output of one neuron. The glia is not learned, however the neurons are learned by BP algorithm. The neuron output dynamically changes, thus the time length of learning term is dynamically changed with the iterations.
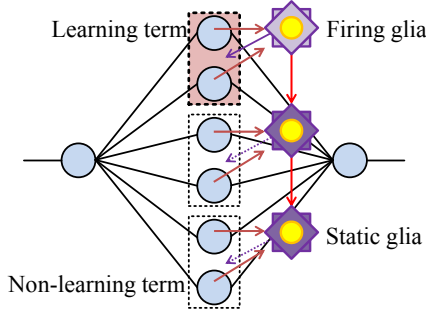

Figure 1: Proposed MLP.

Next, we show the flow of the learning of the proposed MLP in Fig. 2. In this example, one group is composed of two neurons. Every group is connected with one glia. By this glia, the time length of learning term is decided, thereby the time length of learning term is different each other. The learning term and the non-learning term are changed with iterations. During the learning term, the neurons are learned by BP algorithm. On the other hand, the weights of connections between the hidden-layer neuron and the input-layer neurons are not updated. First group goes into the learning term. Other groups are in the non-learning term. Second group goes into the learning term, then the first group remain the learning term. Every group repeats changing the learning term and the non-learning term. When the final group finishes the learning term, the first group starts the learning term

again. The neurons' outputs are changed by learning, thereby the time length of learning term is different from the previous time length.
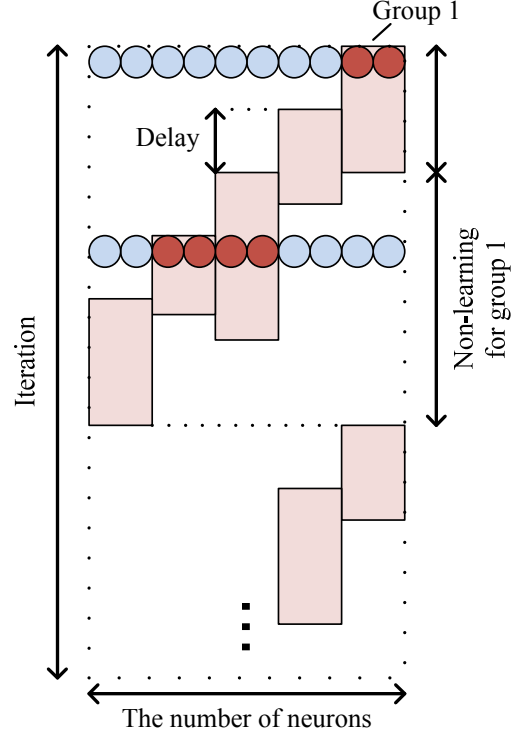

Figure 2: Time flow of the learning term and non-learning term.

3. Simulations

In this section, we show the simulation results of the proposed network. We use the Two-Spiral Problem (TSP) for learning task. The TSP is a famous task for the artificial neural network [10]. It is linearly-inseparable problem, thereby it has a high nonlinearity [11]. The MLP receives the coordinates of the spirals for the inputs and learns the corresponding classifications. In this simulation, the MLP is composed of the neurons (constructed 2-40-1). The iterations are 1000000 times. Figure 3 shows the two spirals for the MLP. In this figure, the spirals are composed of 130 points. For the index of the error, we use the Mean Square Error (MSE) for both simulation results. The MSE is described by Eq. (2).

$$MSE = \frac{1}{P} \sum_{n=1}^{P} (T_n - O_n)^2, \qquad (2)$$

where P is the number of the pairs of the input and the supervised value, T is a supervised value, O is an output of the MLP.
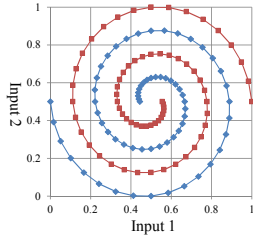
Figure 3: Two-spiral problem.

3.1 Learning performance

We compare three different MLPs which are the proposed MLP, the previous proposed MLP [9], and the standard MLP. The previous proposed MLP is similar to the proposed MLP. The neurons in the hidden-layer are periodically switched between the learning term and non-learning term. However, the time length of the learning term is constant value. Thus, this MLP becomes the learning in a higher rate of periodic. The standard MLP does not have the external unit, thus this MLP often falls into local minimum.

Figure 4 shows an example of the learning curves of three MLPs. The learning curve of the standard MLP is converged earlier because this MLP is trapped into the local minimum. The learning curve of the previous proposed MLP oscillates to about 50000 times. By this oscillation, this MLP can find a better solution than the standard MLP. However, the learning curve converges over 60000 times. The proposed MLP can reduce the error the best of all. Moreover, the oscillation of the curve is observed all iterations. From these result, we can say that the proposed MLP obtains the energy for escaping out from the local minimum by the glial network all iterations.
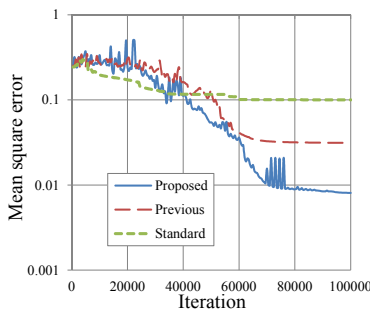

Figure 4: Learning curves.

Table 1 shows the statistic result of the MLPs. From this result, the proposed MLP has the best of all for the average of error. However, the maximum error is a worse than the previous MLP. For this reason, we consider that the glias change the time length of the learning term. The time length of learning term become too small, thus the overlap of the learning term is not happened.

Table 1: Learning performance.

	Ave.	Min.	Max.	Std. Dev.
Proposed	0.0239	0.0003	0.2426	0.0387
Previous	0.0312	0.0002	0.1620	0.0364
Standard	0.0854	0.0006	0.2463	0.0558

3.2 Parameter characteristics

Next, we show the parameter characteristics of the proposed MLP. We define the some parameters of the proposed MLP. The performance of the proposed MLP is changed according to change of the parameters. We change three kinds of parameters which are the number of neurons in a same group, the delay of start time of learning term, and the maximum time length of learning term. Figures 5-7 show the parameter characteristics. Each figure is result for different number of neurons in the same group. In Fig. 5, the MLP performance is better when the delay of start time of learning term is smaller. The dependency of the delay is changed according to the increase of the number of neurons in the same group. When the time length of learning terms is increased, the error is almost reduced. However, the errors increase over a point. From these results, we consider that amount of the overlap of learning term is important for the MLP learning performance.
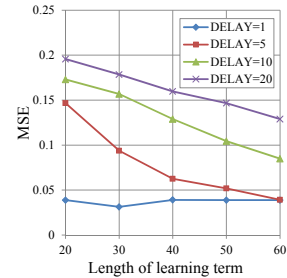

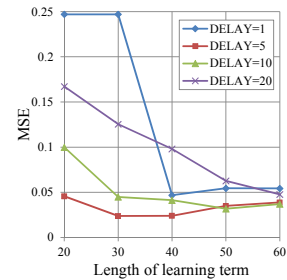Figure 5: Parameter characteristics. (The number of neurons in the same group is 2.)

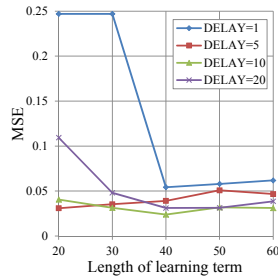Figure 6: Parameter characteristics. (The number of neurons in the same group is 5.)

Figure 7: Parameter characteristics. (The number of neurons in the same group is 10.)

Finally, we show the performance change for a ratio of the time length of learning term to all iterations in Fig. 8. This value means the length of overlap of learning term. We divide five different range of value and calculate the average of the error. From this figure, the performance improves to 0.4-0.6, after that the performance decreases over 0.4-0.6. We can see that the proposed MLP has high dependency for the time length of overlap of learning term. Thus, when we use the proposed MLP, we need to consider the time length of overlap of learning term.
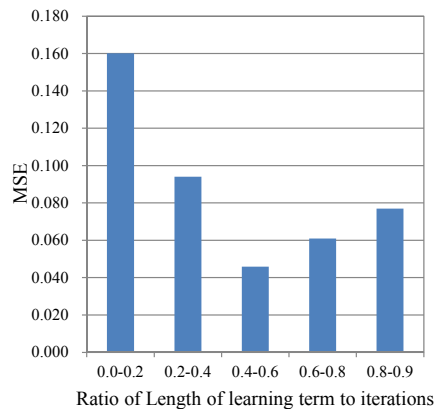

Figure 8: Learning performance for time length of overlap of learning term.

4. Conclusions

In this study, we have proposed the glia-neuron network with group learning of hidden-layer learning neurons. In this model, the neurons in the hidden-layer is decomposed to some learning group. Each group is connected with the glia. Each group has the learning term and non-learning term which are switched according to the connecting glias. The time length of learning term is changed by the glial response and the glial responded is decided by integration of the neuron output in the connecting neurons. We consider that the relationships between the glia and the neuron im-

prove the MLP performance. By the solving TSP, we confirmed the glial-neuron network improves the MLP learning performance, moreover the MLP has high dependency for the time length of overlap of learning term.

Acknowledgment

References

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

[2] S. Kriegler and S.Y. Chiu, "Calcium Signaling of Glial Cells along Mammalian Axons," *The Journal of Neuroscience*, vol. 13, pp. 4229-4245, 1993.

[3] S. Ozawa, "Role of Glutamate Transporters in Excitatory Synapses in Cerebellar Purkinje Cells," *Brain and Nerve*, vol. 59, pp. 669-676, 2007.

[4] M.P. Mattoson and S.L. Chan, "Neuronal and Glial Calcium Signaling in Alzheimer's Disease," *Cell Calcium*, vol. 34, pp. 385-397, 2003. pp. 11023-11028, Mar. 2003.

[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 U.S.A*, vol. 100,

[6] G. Perea and A. Araque, "Glial Calcium Signaling and Neuro-Glia Communication," *Cell Calcium*, vol. 38, pp. 375-382, 2005.

[7] N. Takata, T. Mishima, C. Hisatsune, T. Nagai, E. Ebisui, K. Mikoshiba, and H. Hirase, "Astrocyte Calcium Signaling Transforms Cholinergic Modulation to Cortical Plasticity In Vivo," *The Journal of Neurocience*, vol. 31, pp. 18155-18165, Dec. 2011.

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

[9] C. Ikuta, Y. Uwate, Y. Nishio, and G. Yang, "Multi-Layer Perceptron Decided Learning Neurons by Regular Output Glias," *Proc. NOLTA'12*, pp. 719-722, Oct. 2012.

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

[11] H. Sasaki, T. Shiraishi and S. Morishita, "High precision learning for neural networks by dynamic modification of their network structure," *Dynamics & Design Conference*, pp. 411-1–411-6, 2004.