Investigation of Multi-Layer Perceptron with Propagation of Glial Pulse to Two Directions

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Abstract— **A glia is nervous cell which exists in a brain. The glia can transmit signal to other glias and neurons by change of ions' densities. We have an interest in this feature of the glia. We consider that we can apply this feature to an artificial neural network.**

In this study, we propose a Multi-Layer Perceptron (MLP) with propagation of glial pulse to two directions. The proposed MLP has the glias in a hidden layer. The glias are connected with neurons and are excited by the outputs of neurons. The exciting glias generate pulses and the pulses affect neurons' thresholds and neighboring glias. We consider that the MLP obtains the relationships of position of neurons in the hidden layer and this information give good influence to the MLP leaning. We confirm that the proposed MLP has better learning performance than the conventional MLP. Moreover, we confirm that the performance of the proposed MLP is changed by some conditions of propagation of the glial pulse.

I. Introduction

Applications of neurons have been investigated for a long time. However, the glias have not attracted attentions, because the glias can not use an electric signal. Recently, some researchers discovered that the glias transmitted signals by using the ions [1][2]. The glias are considered to be important for the brain works. Especially, Ca^{2+} can change a membrane potential of the neuron. We consider that the glias can be applied to the artificial neural network.

In the previous study, we proposed a pulse glial chain from the features of the biological glia [3]. In that model, one glia generates a pulse to be excited by the output of the connecting neuron. After that, the next glia is excited and generates the pulse. The pulse propagates to other glias by the glial chain. We connected the pulse glial chain to the Multi-Layer Perceptron (MLP). We confirmed that the MLP with pulse glial chain had better learning performance than the conventional MLP. However, we assumed that the only one glia was excited by the output of the connecting neuron, and that the pulse propagated to one direction.

In this study, we propose MLP with propagation of glial pulse to two directions. All glias are connected with the neurons and are excited by outputs of the connecting neurons. The generated pulses excite glias on both sides. We connect the glias to the neurons in a hidden layer and the outputs of the glias influence the threshold of neurons. Because the Ca^{2+} can change the membrane potential of the neuron in biological system [5][6]. We consider that the glias give the relationships of position of neurons in the hidden layer. By the simulations, we show the learning performance and the parameters dependency of the proposed MLP.

II. Proposed Method

The MLP is the most famous feed forward neural network. This network is composed of layers of neurons and its outputs are controlled by the weights of connections. In general it is learned by Back Propagation algorithm (BP) which was proposed by D.E. Rumelhart [4]. We connect the glias to the neurons in the hidden layer. We show the proposed MLP in Fig. 1.

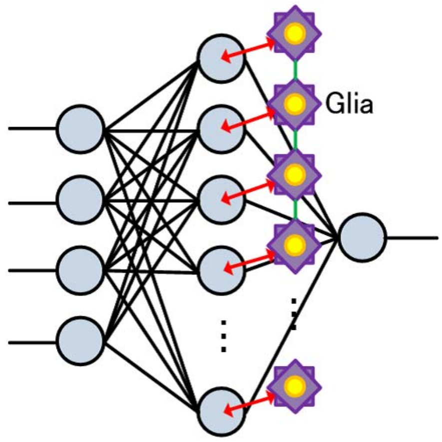

Fig. 1. MLP with propagation of glial pulse to two directions.

A. Glial Pulse

Currently, the glia attracts researchers attentions in the biological or the medical fields. Because the glia has several important works in the brain. Especially, the glia can change the Ca^{2+} density and this Ca^{2+} density become pulse response [7][8]. The Ca^{2+} change the threshold of the neuron. Moreover, this influence propagates to a wide range in the brain.

In this study, we propose the glial pulse which propagates to two directions. The glial pulse is inspired from the features of biological glia. All glias are connected the neurons in the hidden layer and generate pulses by the outputs of the connecting neurons. We define an output function of the glia in Eq. (1).

$$\psi_i(t+1) = \begin{cases} 1, & \{(\theta_n < y_i \cup \psi_{i+1,i-1}(t - i * D) = 1) \\ & \cap (\theta_g > \psi_i(t))\} \\ \gamma\psi_i(t), & else, \end{cases} \quad (1)$$

where ψ is an output of a glia, γ is an attenuated parameter, y is an output of a connecting neuron, θ_n is a glia threshold of excitation, θ_g is a period of inactivity, and D is a delay time of a glial effect. The glias do not learn by BP algorithm, however, the neurons are learned by BP algorithm. Thereby, the generation pattern of glial pulse dynamically changes during the MLP learning.

Figure 2 is an example of glial pulses for obtained from the simulations. During (a) in the figure, the 2nd glia is excited, after that the 1st glia and the 3rd glia are excited by the effect of the 2nd glia. The 2nd glial effect propagate to other glias, however, the 9th glia excite own before to be propagated the effect of the 2nd glia. Thereby, the pattern of pulse is not clearly stepwise. In the center of (a), the 3rd glia is excited. This effect propagate to the 2nd glia, however, this effect does not propagate to the 4th glia. Because the 4th glia has the period of inactivity when the 3rd glial effect propagate to the 4th glia. During (b), the 6th glia is excited first. The 6th glial effect propagates to its neighboring glias. We can see that the generation pattern of glial pulses dynamically changes during MLP learning.

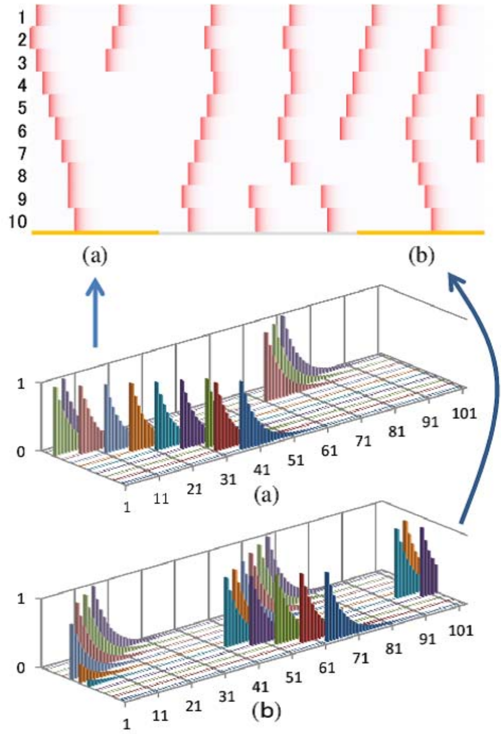

Fig. 2. An example of glial pulses ($D = 5$).

B. Updating Rule of Neuron

The neuron has multi-inputs and single output. We can change the neuron output by tuning weights of connections. The standard updating rule of the neuron is defined by Eq. (2).

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

where y is an output of the neuron, w is a weight of connection, x is an input of the neuron, and θ is a threshold of neuron. In this equation, the weights of the connections and the thresholds of neurons are learned by BP algorithm. Next, I show a proposed updating rule of the neuron. We add the glial effect to the threshold of neuron. This updating rule is used to the neurons in the hidden layer and is described by Eq. (3).

$$y_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t) + \alpha\psi_i(t)\right), \quad (3)$$

where α is weight of glial effect. We can control the glial effect by changing α. In this equation, the weight of connection and the threshold are learned by BP algorithm as same as the standard updating rule of the neuron. However, we fix the glial effect α in this algorithm.

Equations (2) and (3) use a sigmoidal function as the activating function which is described by Eq. (4).

$$f(a) = \frac{1}{1+e^{-a}}. \quad (4)$$

III. Simulation

In this section, we confirm the learning performance of the proposed MLP. Moreover, we show features of the proposed MLP for some conditions. We use five different MLPs, which are

(1) The conventional MLP
(2) The MLP with random timing pulses
(3) The MLP with same timing pulses
(4) The MLP with pulse glial chain
(5) The MLP with propagation of glial pulse to two directions (proposed)

In the MLP with random timing pulses, this MLP is given the pulses to the thresholds of neurons at random timing. The random timing pulses are decorrelated each other. The MLP with same timing pulses is given the pulses which are generated at same timing.

A. Simulation Task

The MLPs learn the classifications of two different chaotic time series. Both chaotic time series are generated by a skew tent map. The skew tent map is defined by Eq. (5).

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

The oscillation pattern of the skew tent map is changed by A. We normalize the chaotic time series of the skew tent map between 0 and 1. Because our MLP use the value between 0 and 1. Figure 3 is one of the learning data.

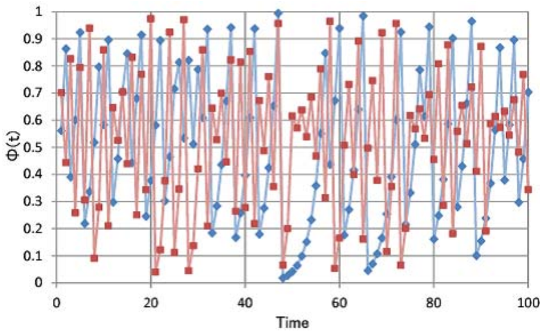

Fig. 3. One of the learning data.

B. Simulation Results

In this simulation, the MLPs learn 50000 times during the one trials. We use 10 pairs of different A. We simulate the 100 trials from different initial weights of connections for each pair of different A. We use the Mean Square Error (MSE) to as a measure of performance. It is described by Eq. (6).

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(T_n - O_n)^2, \tag{6}$$

where N is a number of learning data, T is a target value, and O is an output of MLP.

1) Learning Performance: We compare the five different MLPs. We show the results of MLPs in Table I. From this table, we can see that the learning performance of the proposed MLP is the best of all. The learning performance of the conventional MLP is the worst. The leaning performance of the MLP with same timing pulses is worse than the MLP with random timing pulse. We consider that the MLP with same timing pulses is given too much energy from the glias. The proposed MLP and the MLP with pulse glial chain have better learning performance than the MLP with random timing pulses. We consider that the proposed MLP and the MLP with pulse glial chain have the information of the position of neurons. In the proposed MLP, all glias can generate pulses by outputs of each connecting neuron. Thus, the proposed MLP can change pattern of pulses more dynamically than the MLP with pulse glial chain.

Figure 4 is an example of learning curves of the MLPs. These learning curves are similar result to the Table I. Moreover, the convergence of the proposed MLP is the fastest of all.

TABLE I

LEARNING PERFORMANCE.

	Avg.	Min.	Max.	St. Dev.
(1)	0.00287	0.00002	0.10026	0.00802
(2)	0.00271	0.00001	0.07520	0.00566
(3)	0.00279	0.00002	0.07537	0.00579
(4)	0.00252	0.00001	0.07518	0.00500
(5)	0.00238	0.00001	0.02517	0.00443

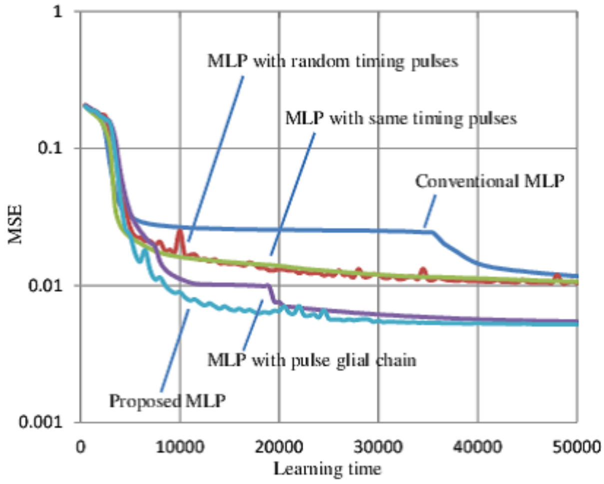

Fig. 4. An example of leaning curves of MLPs.

2) Parameters Dependency: Next, we show a change of the learning performance of the proposed MLP by some parameters. Figure 5 is the change of the learning performance for different α and θ_g in Eq. (1). α is the weight of the glial effect and θ_g is the period of inactivity. When θ_g becomes lager, the generation span of the pulse of the glia becomes longer. From this result, the MLP has the high acceptable amount of α as lager θ_g. Because the MLP can learn the true target value during the period of inactivity. In the large θ_g, the period of inactivity is long, thus, the MLP receives the large glial effect, it can learn the true target value.

Next, we show a learning performance for each θ_n in Fig. 6. θ_n is glial threshold of excitation. When the θ_n is small, the glia can be excited easily. However, the glias can not change the pattern of pulses, because most of glias are excited by the connecting neurons. From this figure, we can see that the MLP has high learning performance as θ_n between 0.8 and 0.9. When θ_n is 0.95, the the MSE becomes large. The MLP cannot obtain enough energy from glias.

Figure 7 is a learning performance of the proposed MLP for different D. D is a delay time of glial effect. If the D becomes larger, the propagated pulses are generated more different timing. From this result, the MLP learning performance is high as $D = 1$ and $D = 9$. In the case of $D = 1$, the pulses are generated delay 1 leaning time. Near glias generate pulses at similar timing and the MLP is given high energy at one learning time. In the case of $D = 9$, two glias are sometimes excited at the same timing. Because the glias finish the period of inactivity earlier than propagating pulses from far glias. The glias which finished the period of inactivity can generate the new pulses.

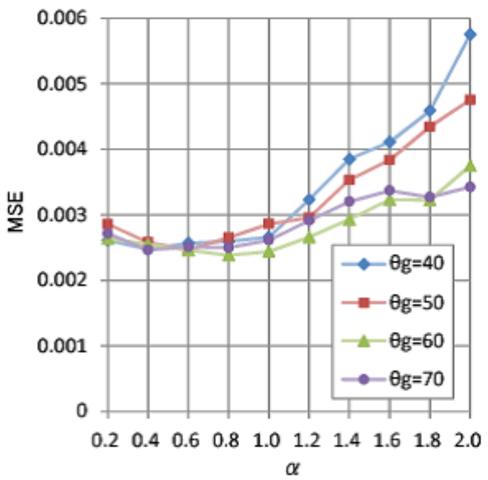

Fig. 5. Leaning performance between α and θ_g.

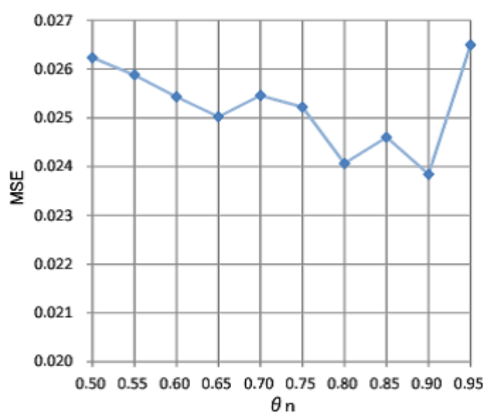

Fig. 6. Leaning performance as different θ_n.

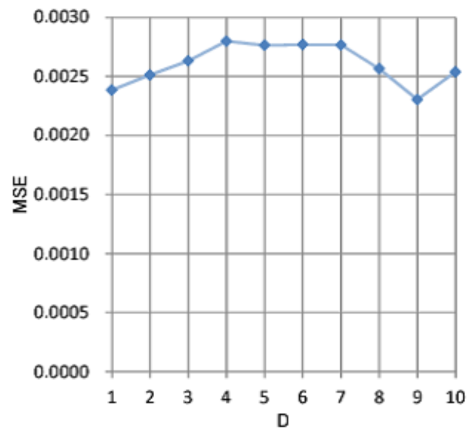

Fig. 7. Leaning performance as different D.

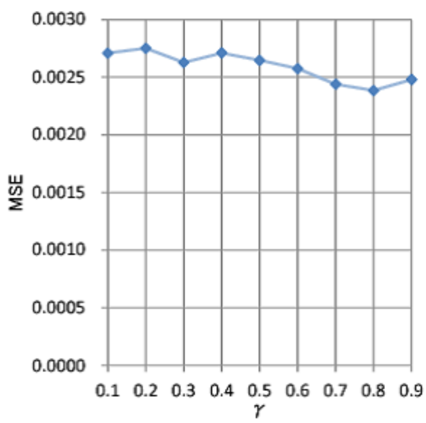

Fig. 8. Leaning performance as different γ.

Finally, we show the learning performance of the MLP for different γ. γ is the parameter of attenuated pulse. When the γ becomes smaller, the pulses are attenuated more rapidly. For small γ, glial effects appeared when neighboring glias generated pulses. We consider that the learning performances are worse for small γ. Moreover, the leaning performance becomes high when γ is large value. In the case of $\gamma = 9$, the MLP has the highest learning performance. However, the learning performance becomes worse for $\gamma = 0.95$. We consider that the attenuation of the pulses are too slowly, thereby, the outputs of the glias cannot become pulses.

IV. Conclusions

In this study, we have proposed the MLP with propagation of glial pulse to two directions. It is inspired from features of biological glia. All glias generate the pulse when the glias are excited by the outputs of the connecting neurons. The pulses are propagated by glia, after that, the pulses influence the threshold of neurons. We connected the glias to the neurons in the hidden layer of MLP. We confirmed that the MLP with propagation of glial pulse to two directions had better learning performance than the conventional MLP. From the simulations, we showed that the MLP obtained the high learning performance by to be given relationships of position of neurons. Moreover, we investigated dependency of parameters of proposed MLP. We confirmed that the learning performance of proposed MLP could be controlled by changing parameters.

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