Improvement of Multi-Layer Perceptron by Pulse Glial Network with Dynamic Period of Inactivity

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Abstract— **In this study, we propose a Multi-Layer Perceptron (MLP) with pulse glial network having dynamic period of inactivity. We connect glias to neurons in a hidden-layer. The glia is excited by the connecting neuron output. Then, the glia generates a pulse. The pulse is propagated to the connecting neuron and the neighboring glia. In the previous method, we fix a period of inactivity. The period of inactivity decides the frequency of the pulse generation. Thereby, the pulse generation pattern often becomes periodic. We consider that it is similar to the local minimum. In this network, the period of inactivity of the glia is dynamically changed according to a pulse generation time. By varying the period of inactivity, the pulse generation pattern obtains the diversity. We consider that this diversity of the pulse generation pattern is efficiency to the MLP performance. By the simulation, we confirm that the proposed MLP improves the MLP performance than the conventional MLP.**

I. Introduction

The neuron and the glia make a higher brain function. The neuron can transmit an electric signals each other. On the other hand, the glia was considered to an accessory cell of the neuron. However, some researchers discovered that the glia has important functions [1][2]. The glia can transmit signal by using ions concentrations which are a glutamate acid, an adenosine triphosphoric acid (ATP), calcium (Ca^{2+}), and so on [3]. These ions are also used in a gap junction of the neuron. Thus, we consider that the glia functions closely relate to the brain's information processing.

The glia-neural network is important for a detailed investigation of the brain works. However, the brain research is mainly about the neuron. Especially, the application of the glia has not almost investigated. We therefore applied the glia characteristics to a Multi-Layer Perceptron (MLP) for the application of the glia. The MLP is a famous artificial neural network. This network is composed of layers of neurons. The MLP is generally learned by Back Propagation (BP) algorithm [4]. By this learning, the MLP can be applied to a pattern learning, a data mining, and so on. However, the BP algorithm has a local minimum problem because this learning algorithm uses the steepest decent method. The MLP does not have the connections in the same layer. The neurons connect to different layer of neurons thus the neurons do not correlate in the same layer.

In this study, we propose the MLP with pulse glial network which has dynamic period of inactivity. We introduce the dynamic period of inactivity to each glia. If the glia is excited by the connecting neuron output, the glia cannot be excited again during the period of inactivity. The previous model has same time length of the period of inactivity, thereby the generation pulse pattern becomes the same cycle. In this method, the time length of the period of inactivity is varied to a short when the glia is continuously excited. The glia which is excited at short interval, obtains different pulse generation cycle. We consider that the varying the period of inactivity breaks the periodic pulse generation. The network learning obtains a diversity. By the computer simulation, we show that the pulse generation pattern becomes the diversity, moreover proposed network obtains a better performance than the conventional method.

II. Proposed Method

In this study, we propose the MLP with pulse glial network having dynamic period of inactivity. We connect the glias to the neurons in the hidden-layer. The glia makes the different network from the neural network. Firstly, the glia receives the connecting neuron output. If it is over the excitation threshold of the glia, the glia is excited. The excited glia generates the pulse. This pulse can obtain a negative value and a positive value according to the neuron output. After that, the pulse is input to the connecting neuron threshold. Moreover, the pulse influences to the neighboring glias. The neighboring glias are also excited by this pulse independent from the connecting neuron output. In the previous method, we fix the period of inactivity. The period of inactivity decides the cycle of the pulse generation. Then the pulse generation often became the periodic. We consider that it reduces the possibility of escaping out from the local minimum. In the proposed method, we vary the period of inactivity according to the glia excitation. When the same glia is continuously excited by the connecting neuron, the period of inactivity of this glia becomes a short. The glia obtains the different period of inactivity each other with time. Thus, this glia exits the periodic pulse generation because the neighboring gila does not finish the period of inactivity when this glia finishes the period of inactivity.

A. Glia response

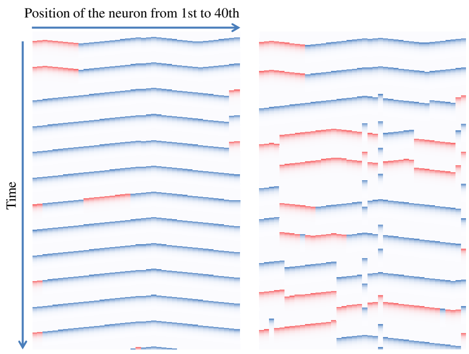
The glia has two different states which are the positive response and the negative response. We define the output function as the positive response of the glia in Eq. (1).

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

where ψ is an output of a glia, i is a position of the glia, θ_n is a glia threshold of excitation, y is an output of a connected neuron, D is a delay time of a glial effect, τ is local time of the glia during a period of inactivity, θ_g is a length of the period of inactivity, γ is an attenuated parameter. In the proposed method, the length of the period of inactivity is varied according to the pulse generation. If the glia is continuously excited by the connecting neuron output, the length of the period of inactivity becomes a short. Moreover, if the glia is excited by the neighboring glia pulse, the period of inactivity of this glia returns to original time length of the period of inactivity.

B. Pulse propagation

Figure 1 shows an example of the pulse generation and a propagation. In this figure, some glias are excited and these generate the pulses. If the glia receives the large output of the connecting neuron, this glia generates the positive pulse which is shown in blue area. If the glia receives the small output of the connecting neuron, this glia generates the negative pulse which is shown in red area. After that this pulses are propagated to the other glias. Both pulse generations are similar pattern at first. In the case of (a), we can observe a small change of the pulse generation pattern. The pulse generation pattern is converged with time. On the other hand, the pulse generation pattern (b) piecemeal varies from (a). Moreover, the pulse generation pattern (b) varies for a long time than (a). From the figure, the proposed network breaks the periodic pulse generation and makes the diversity.



(a) Previous pulse generation (b) Proposed pulse generation

Fig. 1. Pulse generation and propagation. (a) The pulses are generated by the previous glial network. (b) The pulses are generated by the proposed glial network.

C. Updating rule of neuron

The neuron has multi-inputs and a single output. We can change the neuron output by tuning the 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 weight of connection and the threshold of the neuron are learned by BP algorithm. Thus, the neuron output is depended on the BP learning. 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 neurons in the hidden layer. It 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 a weight of the glial effect. We can change the glial effect by change of α. In this equation, the weight of connection and the threshold are changed by BP algorithm same to the standard updating rule of the neuron. However, the glial effect is not changed. It is updated by Eq. (1).

Equations (2) and (3) are used a sigmoidal function to an activating function which is described by Eq. (4).

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

where a is an inner state.

III. Simulations

We compare five kinds of the MLPs which are the standard MLP (1), the MLP with random noise (2), the MLP with pulse glial chain (3), the MLP with pulse glial network (the period of inactivity is random) (4), and the MLP with pulse glial network (the period of inactivity is varied according to the pulse generation) (5). Every MLP has same number of neurons and layers. The MLP is composed of 2-40-1 neurons. We obtains the statistic result from 100 trials. Every trial has different initial conditions. One trial has 50000 iterations. We use Mean Square Error (MSE) for the error function. where N is a number of learning data, T is a target value, and O is an output of MLP. We obtain results which are an average error, a minimum error, a maximum error, and a standard deviation of the results. We use a Two-Spiral Problem (TSP) for the simulation task. The TSP is famous task for the artificial neural network [5].

A. Statistic results

Firstly, we show the learning performance of the spirals. The learning performance means the fitting between the output of the MLP and the supervised classification. The statistic result shows in Table I. We can see that the standard MLP often traps into the local minimum. Thereby, the average of error is the worst of all. The result of the MLP with random noise is similar to the standard MLP. From this result, the uniformed random noise is not efficiency to the TSP. Other three MLPs improve the performance from the result of the standard MLP. Especially, the MLP with pulse glial chain and the proposed MLP have a good learning performance. Moreover, the maximum error of the proposed MLP is the best of all. From this result, we can say that the proposed MLP has a high ability for escaping out from the local minimum. Thereby, our proposed MLP reduces an initial valued dependence. It means that we can stably obtains the better result.

TABLE I
LEARNING PERFORMANCE.

	Average	Minimum	Maximum	Std. Dev.
(1)	0.12269	0.00831	0.23857	0.05554
(2)	0.10847	0.00047	0.24278	0.05742
(3)	0.01990	0.00067	0.11664	0.02226
(4)	0.05546	0.00134	0.14481	0.03608
(5)	0.01414	0.00052	0.04851	0.01313

B. Learning curves

Fig. 2 shows learning curves of each MLP. The standard MLP converges the error reduction at 25000. It is trapped into the local minimum. The convergence of the error in the MLP with random noise is a slower than the others. However, it reduces the error than the standard MLP. The uniformed random noise has a small efficiency to the learning of the MLP. On the others, these curves have a oscillation during the iterations. Moreover the performance of the error reduction improves. The pulse locally gives the large energy to the network. The pulse helps escaping out from the local minimum. The glia has the period of inactivity. During the period of inactivity, the glia does not generate the pulse again. Thereby, the MLP can search the better solution during the period of inactivity. The error reduction of the proposed MLP is earlier than the others. Thus, the pulse generation pattern influences the learning of the MLP.

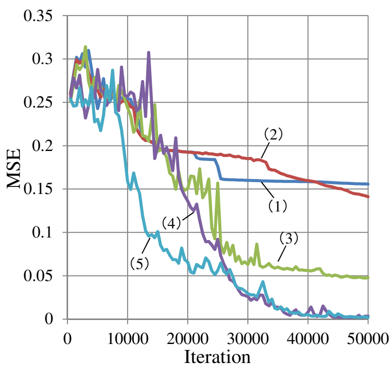


Fig. 2. Learning curve.

IV. CONCLUSIONS

In this study, we have proposed the MLP with pulse glial network having dynamic period of inactivity. The glias are connected with the neuron. The glias generate the pulse according to the connecting neuron output. The generated pulse influences the connecting neuron threshold and the neighboring glia state. In this method, the period of inactivity is varied according to the pulse generation time. If the pulse generation continuously occurs by the connecting neuron output. By this influence, the pulse generation pattern is dynamically changed because the period of inactivity of the glia is different each other. We consider that the glia pulse improves the MLP performance. Actually, we confirm that the proposed MLP obtains a better performance than the conventional MLP.

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