Investigation of Multi-Layer Perceptron with Pulse Glial Chain Including Neurogenesis

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***Abstract*—In this study, we propose Multi-Layer Perceptron (MLP) with pulse glial chain including neurogenesis. In this network, we one-by-one connect glia unit with neurons in a hidden-layer. The glia generates a pulse according to the connecting neuron output. This pulse increases the threshold of the neuron and excites the neighboring glias. The pulse generation frequency is also changed according to the connecting neuron output. Moreover, we introduce a neurogenesis to the network. By the neurogenesis, any neurons are removed and newborn neurons are set to same position. The removed neurons are chosen by the number of pulse generation of the glia, and the newborn neuron has random value in the connection with other neurons. We consider that the unimportant neurons for the learning are removed and the newborn neurons become the important neurons. By computer simulations, we confirm that the proposed MLP obtains a better solving ability than the previous MLP.**

I. Introduction

A glia and a neuron are existing in a human brain. The neuron has been considered to an important cell for a higher brain function. Actually, the neuron can transmit electric signal each other and conduct advanced information processing. On the other hand, the glia was considered to the supporting cell for the neuron. The glia exists between the neurons and a blood vessel and provides necessary nutrients which are carried into the blood vessel to the neurons. Recently, some researchers reported that the glia controls an ion concentration [1]-[3]. The glia uses various kinds of ions such as a glutamate acid, an adenosine triphosphate, a Ca^{2+}, et al. [4]. Among them, we focus on the Ca^{2+}. The glia occurs a Ca^{2+} concentration wave and this wave transmits to other glias, moreover the Ca^{2+} increases a membrane potential of the neuron. Hence, the glia closely relates to the higher brain function.

In this study, we propose a MLP with pulse glial chain including neurogenesis [1] which is extended from the MLP with pulse glial chain based on individual inactivity period [5]. The glias are one-by-one connected with the neurons. The glia receives the connecting neuron output and is excited by this output. The excited glia generates a pulse and this pulse transmits to other glias and the neurons. Moreover, the period of inactivity is dynamically changed by the continuous stimulus from the connecting neuron. In this model, we introduce a neurogenesis to the MLP. The glia count the number of pulse generations. When the number of pulse generations are small number, the connecting neuron is removed. After that, the newborn neuron set to the same position as the removed neuron. By the frequency of the pulse generation, the glia can find the important neurons and the unimportant neuronsn. By the neurogenesis, we consider that the number of contributory neurons for the network performance increase. We confirm that the performance of the proposed MLP improves than the previous MLP, moreover we show the characteristics of the proposed MLP.

[1]We have already reported this method in Proc. of NOLTA'14, pp. 508-511, Sep. 2014. In this study, we add new results to this paper.

II. Proposed MLP

The MLP is a famous feed forward neural networks. In general, the weight of connection is tuned by a Back Propagation (BP) algorithm [6]. The BP algorithm is useful for the learning of the MLP, however this algorithm often falls into a local minimum. In the proposed MLP, we connect the glias with the neurons. The glia is excited by the output of the connecting neuron. Then, the glia generates the pulse. This pulse is input to the connecting neuron threshold and is transmitted to the neighboring glias. The neighboring glias are excited by the transmitted pulse and also generate the pulse. Thereby, the pulse is transmitted into the glial network. Moreover, the period of inactivity of the glia becomes shorter when the glia is excited in continuity. By this process, each glia has a different pulse generation cycle. In the proposed MLP, we introduce the neurogenesis into the neurons in the hidden-layer. The neurogenesis happens at a regular iteration. The removed neuron is chosen by the number of pulse generations of the connected glia. If the number of the pulse generation of the connected glia is smaller than the decided value, the connecting neurons are removed and newborn neurons are connected in the same position. The weight of connection of the newborn neuron is decided at random.

A. Updating rule of neuron

We show a proposed updating rule of the neuron. We add the glial pulse to the threshold of neuron. We use this updating rule to the neurons in the hidden layer. It is described by Eq. (1).

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

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 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. The glial is independent from BP algorithm, thus the weight of the glial effect is not changed by BP algorithm. On the other hand, we use the standard updating rule of the neuron in the input-layer and the output-layer.

B. Glial pulse

The glia has a response to the output of the connecting neuron. The glia response is described by Eq. 2.

$$\psi_i(t+1) = \begin{cases} 1, & \{(\theta_n < y_i \cup \psi_{i+1,i-1}(t - i * D) = 1) \\ & \cap (\tau_i \geq \theta_{gi})\} \\ \gamma\psi_i(t), & else, \end{cases} \quad (2)$$

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. When the output of the connecting neuron is larger than the excitation threshold of the glia, the glia generates pulse. Then, the output of the glia ψ has 1. After that the pulse decreases in an exponential fashion. The pulse excites the neighboring glia which has a delay of the iteration D.

In this model, the glia has a dynamic period of inactivity. The dynamic period of inactivity is described by Eq. (3).

$$\theta_{gi}(t+1) = \begin{cases} \theta_{gi}(t) - 1, \psi_{gi}(t) = 1 \cap \psi_{gi}(t - \theta_{gi}) = 1. \\ \theta_{gi}(0), else, \end{cases} \quad (3)$$

If the glia continuous generates the pulse, the length of the period of inactivity becomes shorter. In other case, if the glia stops the pulse generation, the length of the period of inactivity becomes a original value. By the change of the period of inactivity, each glia has different period of inactivity, thereby the glial network obtains the various pulse generation pattern. We show an example of the change of the period of inactivity in Fig. 1. In this figure, we use $\theta_g(t) - 5$ in each change step of the period of inactivity for an understandability. The pulse generation frequency becomes shorter according to the change of the period of inactivity.

C. Neurogenesis

The neurogenesis happens into the adult human brain, moreover some researchers reported that the connecting position of the newborn neuron is decided by the glia [7]. In the proposed model (shown as Fig. 2), we introduce the neurogenesis to the neurons in the hidden-layer. We count the number of excitations of the glia. If the number of excitations of the glia is smaller than the constant value, the neuron is removed and the newborn neuron is connected in the same position. We give the random value to every weight of connection of the newborn neuron.

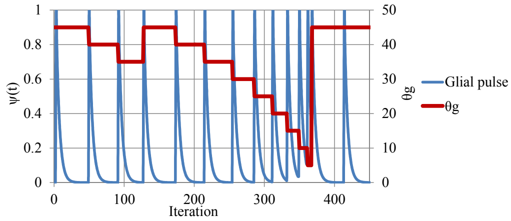

Fig. 1. The correlation between the pulse generation and the period of inactivity.

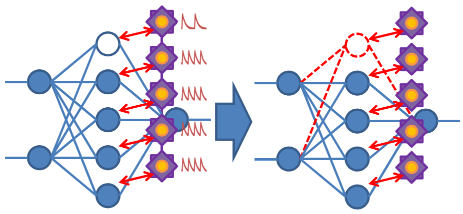

Fig. 2. Neurogenesis.

III. Simulation

In this study, we use a Two-spiral Problem (TSP) for the simulation task.The TSP is a famous task for the artificial neural network and has a high nonlinearity [8] [9]. In this simulation, we use 130 spiral points for the learning. We input the coordinates of the spirals, and the MLP learns the classification of the spirals. In the TSP, the difficulty and the nonlinearity increase according to the number of spiral points.

In this simulation, we compare the three kinds of the MLPs which are;

(1) The standard MLP.
(2) The MLP with pulse glial chain based on individual period of inactivity.
(3) The MLP with pulse glial chain including neurogenesis.

The standard MLP does not have an external unit, thus this MLP often falls into a local minimum. The MLP with pulse glial chain based on the individual period of inactivity is the previous model which was proposed in WCCI'14. We use a Mean Square Error (MSE) for the evaluation of the performance.

A. Learning performance

We obtain the result from 100 trials, and one trial has 100000 iterations. In every trial, we give different initial condition. In this simulation, the neurogenesis happens at 50000 iterations. Then, if the number of pulse generations is small, the neuron is removed and we set a newborn neuron. From the simulation result, we obtain four kinds of evaluation indexes which are average, minimum, maximum, and standard deviation. We show the learning performance of the MLPs in Table I. From this result, the standard MLP (1) is the worst of all, because this method often falls into local minimum. The proposed MLP (3) improves the performance from the previous MLP (2). We consider that the unimportant neurons are removed by the neurogenesis, and the newborn neuron works on the learning.

TABLE I
LEARNING PERFORMANCE OF SPIRAL OF 130 POINTS.

	Average	Minimum	Maximum	Std. Dev.
(1)	0.09604	0.00027	0.23087	0.05751
(2)	0.00904	0.00037	0.04685	0.01161
(3)	0.00827	0.00087	0.04633	0.00975

B. Dependency on the number of removed neurons

Next, we obtain the average errors in different number of removed neurons which is shown in Fig. 3. The average error decreases to 15 removed neurons after that the average error increases. From this result, we can say that many unimportant neurons exist in the network and the unimportant neurons are effectively removed by the neurogenesis.

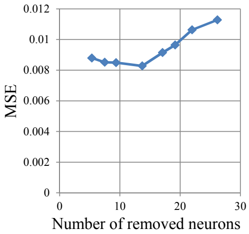

Fig. 3. The dependency on the number of removed neurons.

C. Dependency on the number of neurons in the hidden-layer

We change the number of neurons in the hidden-layer and compare the average of error. The dependency of the number of neurons is shown in Fig. 4. In general, the learning performance of the MLP depends on the number of neurons. However, the average error of the standard MLP does not change by the number of the neurons. On the other hand, the MLP with pulse glial chain based on individual period of inactivity and the proposed MLP decrease the average error according to increasing of the number of neurons. The difference of the average error between the MLP with pulse glial chain based on individual period of inactivity and the proposed MLP is small in the small number of neurons. We consider that the proportion of the number of important neurons is lager than the number of the unimportant neurons in small number of neurons. Thereby, the neurogenesis is not efficient to the learning performance in small number of neurons. When the number of neurons increases, the number of unimportant neurons also increases. In the large number of the neurons, the neurogenesis removes many unimportant neurons and set the newborn neurons. Thus, the proposed MLP economizes the neurons than the other MLPs by the neurogenesis in the large number of neurons.

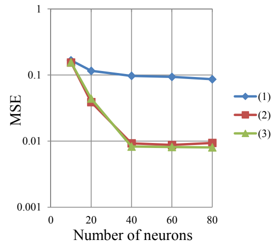

Fig. 4. Dependency of number of neurons.

IV. CONCLUSIONS

In this study, we have proposed the MLP with pulse glial chain including the neurogenesis. In this network, the glias are one-by-one connected with the neurons in the hidden-layer. The glia is excited by the connecting neuron output, and excited glia generates the pulse. This pulse transmits to the other glia and increases the threshold of the neuron. The pulse generation patterns are variedly changed because the period of inactivity of the glia is dynamically chain according to the pulse generation frequency. In addition, the neurogenesis occurs at half of iterations. By the neurogenesis, some neurons are removed and the newborn neurons which has random weights are set in the same position as the removed neurons. The removed neurons are chosen by the pulse generation frequency. The neurogenesis increases the number of the important neurons. By the computer simulation, we confirmed that the proposed MLP obtains the better performance than the previous MLPs.

ACKNOWLEDGMENTS

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