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Neuro-Glia Network with Neurogenesis

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Abstract— In this study, we propose a neuro-glia network with neurogenesis based on a Multi-Layer Perceptron (MLP) with pulse glial chain based on individual inactivity period. This network has a connection between a glia and a neuron in a hidden-layer. The glia generates a pulse and this pulse is propagated to the neurons and the neighboring glias. The pulse generation cycle is dynamically changed by the neuron output. By a frequency of the pulse generation, the glia chooses an important neuron and an unimportant neuron. In the neurogenesis, the unimportant neuron is removed and a newborn neuron is connected in the same position as the removed neuron. We consider that the pulse of the glia gives an energy for escaping out from a local minimum, moreover the number of contributory neurons for the network performance increase by the neurogenesis. We confirm that the proposed MLP has a better performance than the previous MLP and show characteristics of the proposed MLP.

1. Introduction

Brain is composed of two kinds of nerve cells which are a glia and a neuron. The neuron has been investigated about biological characteristics and applications for many years. The neurons connect with other neurons and transmit electric signals each other. On the other hand, the glia was considered to the supporting cell for the neuron. Actually, 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+}, and so on [4]. Among them, we focus on the Ca^{2+}. The concentration of the Ca^{2+} increases by the excited glia and the increasing of the concentration of the Ca^{2+} excites the neighboring glias. The change of the concentration of the Ca^{2+} triggers a chain reaction. Moreover, the glia transmits signals to other glias by the concentration of the Ca^{2+}.

In the previous study, we proposed the Multi-Layer Perceptron (MLP) with pulse glial chain based on individual inactivity period which is inspired from the biological characteristics of the glia [5]. We one-by-one connect the glias with the neurons in the hidden-layer. The glia generates the pulse when the neuron output is larger than the threshold of the excitation of the glia. The generated pulse is transmitted to the connecting neuron and the neighboring glias. The neighboring glias are excited by the transmitted pulse and generate the pulse, thus the pulse is transmitted into the glial network. In the previous MLP, a period of inactivity (interval of the pulse generation) becomes shorter according to the connecting neuron output. Thereby, the pulse generation becomes different pattern in each glia. This change of the pattern in each glia gives variety for the learning of the MLP and improves the learning performance. Moreover, we check the number of pulse generations in each glia during the iterations, thereby important neurons for the network performance are connected with the glias which generate many pulses.

In this study, we propose the neuro-glia network with neurogenesis which is extended from the MLP with pulse glial chain based on individual inactivity period. The glia can find the important neurons and the unimportant neurons by the pulse generation. In this network, the unimportant neurons in the hidden-layer are removed and the newborn neurons are connected in the same position, then the weight of connections defines at random (we call this process 'neurogenesis'). 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 by the computer simulations.

2. Proposed MLP

The MLP is one of feed forward neural networks. This network can be applied to various nonlinear tasks. The output of the MLP is decided by the weight of connection between the neurons. 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 shown as Fig. 1. 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.

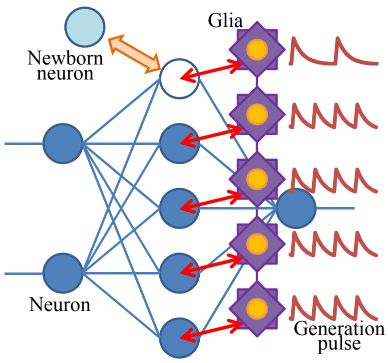

Figure 1: Proposed MLP.

2.1. Updating rule of neuron

The neuron has multi-input and single output. The standard updating rule of the neuron is defined by Eq. (1).

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

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. 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, 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. (2).

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

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. The glial is independent from BP algorithm, thus the weight of the glial effect is not changed by BP algorithm. Equations (1) and (2) uses a sigmoidal function for an activating function which is described by Eq. (3).

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

where a is an inner state.

2.2. Glial pulse

The glia has a response to the output of the connecting neuron. The glia response is described by Eq. 4.

$$\psi_i(t+1) = \begin{cases} 1, & \{(\theta_n < y_i \cup \psi_{i+1,i-1}(t - i * D) = 1) \\ & \quad \cap (\tau_i \geq \theta_{gi})\} \\ \gamma\psi_i(t), & else, \end{cases} \qquad (4)$$

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 the previous study, we proposed the glia which dynamically changes the period of inactivity according to the output of the connecting neuron. If the glia continuously receives the large output from the connecting neuron, the period of inactivity (θ_g) of this glia becomes shorter. Each glia has different period of inactivity, thereby the glial network obtains the various pulse generation pattern. The change of the period of inactivity and the pulse generation are shown in Fig. 2.

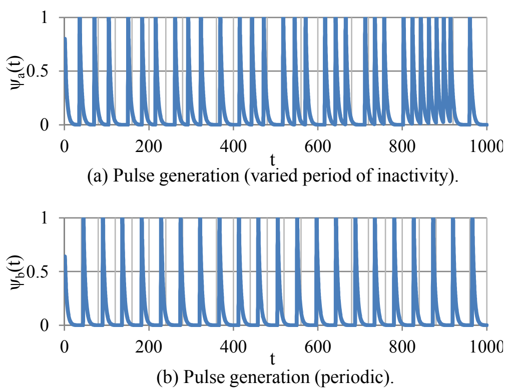

Figure 2: Varying period of inactivity. (a) The frequency of the pulse generation. (b) Periodic pulse generation.

2.3. 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. 3), 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.

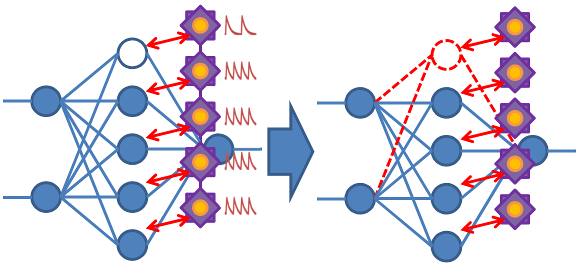

Figure 3: Neurogenesis.

3. Simulation

In this study, we use a Two-spiral Problem (TSP) for the simulation task shown as Fig. 4. The TSP is a famous task for the artificial neural network and has a high nonlinearity [8] [9]. The MLP learns the classification of the spirals.

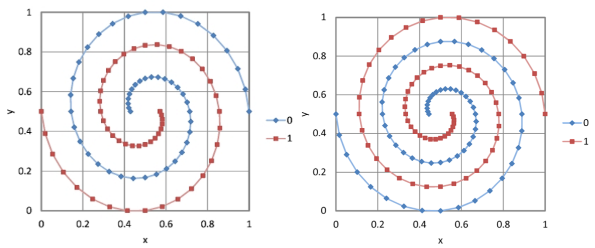

Figure 4: Two-Spiral Problem.

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 neuro-glial network with 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. The MSE is described by Eq. (5).

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(T_n - O_n)^2, \quad (5)$$

where T is a supervised signal and O is a output value of the neuron in the output-layer.

3.1. 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. Firstly, we show a learning performance when the MLP learns the 98 spiral points. The simulation result is shown in Table 1. From this result, the standard MLP is the worst of all in the average. This MLP often falls into a local minimum. Actually, the maximum of the error is the highest of all. The proposed MLP has a better performance than the previous MLP in the average, the minimum, and the standard deviation.

Table 1: Learning performance of spiral of 98 points.

	Average	Minimum	Maximum	Std. Dev.
(1)	0.03443	0.00007	0.18375	0.02422
(2)	0.00340	0.00005	0.04102	0.00845
(3)	0.00188	0.00015	0.03071	0.00517

Next, we show the result when the MLP learns 130 spiral points in Table 2. The result trend is similar to the previous simulation. The proposed MLP has a better performance than the others.

Table 2: 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

3.2. Learning curve

We show an example of the learning curve of the proposed MLP and the previous MLP in Fig. 5. In the proposed MLP, the neurogenesis happens at 50000 iterations. Both learning curves have the same orbit until 50000 iterations. The learning curve of the previous MLP converges. The learning curve of the proposed MLP is also converges at 50000 iterations. However, the error decreases from 50000 iterations. We consider that the unimportant neurons are removed by the neurogenesis, thereby the important neurons increase and the MLP learning performance improves.

3.3. Importance of neurons

In this simulation, we confirm the importance of the neurons in the hidden-layer for the network performance. We remove one neuron in the hidden-layer of the learned MLP and obtain the error between the true value and the output. By this simulation, we can obtain contribution ratio of

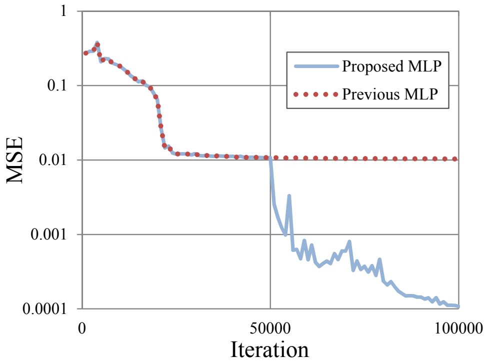

Figure 5: Learning curves.

each neuron for the MLP performance. The result is shown in Fig. 6. (a) shows the frequency of the pulse generation in each neuron to the total iterations. (b) and (c) show the error value for each removed neuron position when we remove one neuron in the hidden-layer. When the error of the output is high, this neuron has high contribution for the MLP performance. Thus, this neuron is the important neuron. We can see that the number of pulse generations correlate to the importance of the neuron. In the previous MLP, half of neurons become the unimportant neuron. On the other hand, some neurons become important neuron in the proposed MLP. We can say that unimportant neurons are chosen and are renewed to newborn neuron, thereby some neurons becomes to the important neuron.

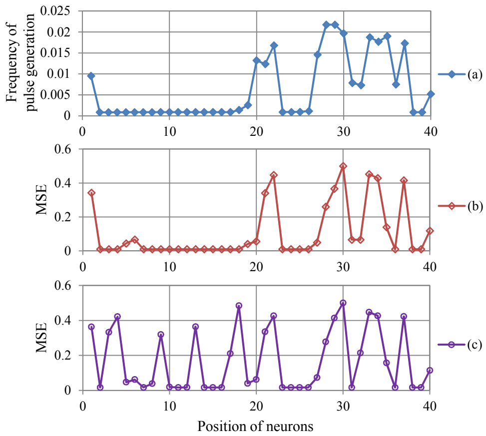

Figure 6: Contribution ratio of each neuron in the hidden-layer. (a) Frequency of the pulse generation. (b) Contribution ration of each neuron in the previous MLP. (c) Frequency of the pulse generation. (b) Contribution ration of each neuron in the proposed MLP.

4. Conclusions

In this study, we have proposed the neuro-glia network with the neurogenesis which is inspired from the characteristics of the biological glia. We connect the glias to the neurons in the hidden-layer. The glia generates the pulse according to the output of the connecting neurons. The pulse is transmitted to the neighboring glias and the threshold of the connecting neuron. The period of inactivity of the glia becomes shorter when the glia continually receives the large output of the connecting neuron. We check the frequency of the pulse generation. When the frequency of the pulse generation is lower than the decided value, this neuron is deleted and the newborn neuron is connected in the same position. By the computer simulation, we confirmed that the proposed MLP obtains the better performance than the previous MLP, moreover, the number of the important neurons increase by the neurogenesis.

Acknowledgments

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