Artificial Neuron-Glia Network Including Random Glia Pulse Generation

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***Abstract*—A human brain is composed of two kinds of cells which are a neuron and a glia. These cells correlate each other and compose a higher brain functions. In this study, we propose an artificial neuron-glia network including including oscillatory glia excitation threshold. This network based on a multilayer perceptron and glias are connected with neurons in a hidden layer. The glia is excited by the output of connected neuron. Then, the glia generates a pulse, and this pulse transmits to neighboring glias and the connected neuron. In this model, we introduce a randomly oscillation to a glia excitation threshold. This oscillation gives a probabilistic glia excitation in near the glia excitation threshold. We consider that the probabilistic glia excitation is efficiency to a network learning. By computer simulation, we confirm that the proposed model has better performance than the conventional models.**

I. Introduction

A human brain has many functions. For a long time, these functions are only composed of neurons. Recently, some researches reported that a glia also related to the brain functions [1][3]. These works confirmed the glia transmits signals to neurons and glias by using an ion concentration. Moreover, the glia has many receptors to ions such as glutamate acid, adenosine triphosphate, calcium [4][6]. Among them, we focus on the calcium ion. The glia transmits a signal by using the change of calcium ion concentration [7][8]. This change of ion concentration also influences a membrane potential of the neuron. Thus, the glia closely relates to the neurons and makes the brain works. We consider that the glia function can apply to an artificial neural network.

In this study, we propose an artificial neuron-glia network including random glia pulse generation which is based on relationships between the neuron and the glia. The glia is connected with the neurons in the hidden layer and is excited by the output of the connecting neuron. The excited glia generates a pulse. This pulse transmits to other glia and neurons in the hidden layer. When the glia receives the pulse, the glia is also excited. In the case of the neuron, the pulse increases the neuron threshold. In this model, we introduce the randomly oscillation to the glia excitation threshold. The excitation threshold oscillates within defined value during a learning. When the learning of the network converges, the output of the neuron is fixity. Thereby, the pattern of the glia pulse generation is also fixed. In the proposed model, the glia can change between a generation and a stopping generation of the pulse by the randomly oscillation of glia excitation threshold. By the change of the pulse generation, the pulse propagation is also changed. We consider that the randomly oscillation of excitation threshold gives more energy to the network. We confirm that the glia improves the network learning performance by using Two-Spiral Problem (TSP).

II. Proposed Network

A proposed network based on a multilayer perceptron. The neurons make layers and have connections with the neurons in the neighboring layers. The proposed network has the glias in the hidden layer shown as Fig. 1.

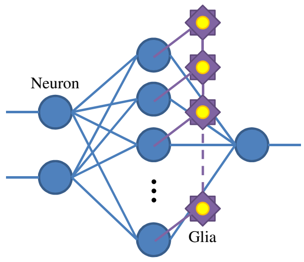

Fig. 1. Proposed network.

A. Random Glia Pulse Generation

The glias are one-by-one connected with the neurons in the hidden-layer. In this model, the glias and the neurons correlate each other. The glia receives the connecting neuron output and is excited by the connecting neuron output. The excitation conditions of the glia are described by Eq, (1).

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

where ψ is an output of a glia, i is a position number of the glia in the hidden-layer, γ is an attenuation parameter

$(0 < \gamma < 1)$, y is an output of a connecting neuron, θ_n is a glia excitation threshold, τ is a time of a previous pulse generation, θ_g is a period of inactivity, and D is a delay time of a glial effect When the connecting neuron output is larger than the glia excitation threshold ($\theta_n(t)$), the glia is excited and generates the positive pulse. And also, when the connecting neuron output is smaller than $1 - \theta_n(t)$ of the glia, the glia is excited and generates the negative pulse. The generated pulse transmits to the neighboring glias and the connecting neuron. The pulse excites the neighboring glias and increases the inner state of the connecting neuron. The neighboring glias also generate the pulse, thereby the pulse transmits to all glias. When the glia generates the pulse, the glia starts the period of inactivity. If this glia receives the neuron output and/or the neighboring glial pulse, the glia cannot be excited again during period of inactivity.

In this study, we introduce the randomly oscillation of glia excitation threshold to the pulse glial chain. The randomly oscillation is described by Eq. (2).

$$\theta_n(t) = r(t) \quad (a < r < b), \tag{2}$$

where r is random function, and a and b is constant value. The value of the excitation threshold oscillates between a and b. We use Mersenne Twister pseudo-random number [9] for the random function. Figure 2 shows example of the relationships between the randomly oscillation of glia excitation threshold and the output of the neurons. We consider three cases of the output of the neuron in the simulation. The output of the neuron (A) does not reach the glia excitation threshold, thereby the connected glia is not excited by this neuron. The output of the neuron (B) is into the amplitude of the randomly oscillation of glia excitation threshold when the output of this neuron is converged. In this case, the connected glia with neuron (B) is stochastically excited. The output of the neuron (C) completely overcomes the randomly oscillation of glia excitation threshold when the output of this neuron is converged. The connected glia with the neuron (C) is excited independent from the randomly oscillation of glia excitation threshold. In the proposed method, several glias are stochastically excited by the randomly oscillation of glia excitation threshold. We consider that the randomly oscillation of glia excitation threshold breaks the periodic pulse generation of the glias, thereby the glias can effectively give the energy to the network.

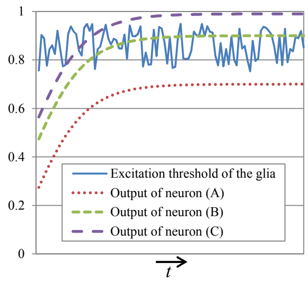

Fig. 2. Relationships between randomly oscillation of glia excitation threshold and the output of the neurons.

B. Updating rule of neuron

The neuron has multi-input and single-output, and we can change the neuron output by tuning the weights of connections between the neurons. The standard updating rule of the neuron is defined as shown in Eq. (3).

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

where y is an output of the neuron, w is a weight of the connection, x is an input of the neuron, and θ is an excitation threshold of the neuron. In this equation, the weight of the connection and the threshold of the neuron are learned based on the BP algorithm. Next, we show the proposed updating rule of the neuron. We add the generated pulse of the glia ψ to the excitation threshold of the neuron. In this study, this updating rule is only used for the neurons in the hidden-layer. The updating rule is described by Eq. (4).

$$y_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t) + \alpha\psi_i(t)\right), \tag{4}$$

where α is a weight of the glial effect. A peek of the generated pulse is changed according to α. We choose an optimal value of α for solving a task by a heuristic search. The generated pulse is independent from the learning of the network, thus this pulse can gives an energy to the network and helps for escaping out from the local minimum. The weight of the connection and the excitation threshold of the neuron are learned by back propagation algorithm (BP) [10]. On the other hand, the glial pulse does not learn by the BP; thus the glia gives the energy to the network when the network falls into local minimum. ψ is updated by Eq. (1). Equations (3) and (4) are used as a sigmoidal function to an activating function of neuron and is described by Eq. (5).

$$f(a) = \frac{1}{1+e^{-a}}, \tag{5}$$

where a is an inner state of the neuron.

III. SIMULATION

We use five kinds of the networks for comparison of the performance.

(1) The standard MLP
(2) The MLP with random noise
(3) The MLP with random timing pulses
(4) The MLP with pulse glial chain
(5) The neuron-glia network including random glia pulse generation

The standard MLP (1) does not have the external unit, thus this MLP often falls into the local minimum. The MLP with random noise (2) has a uniformed random noise in the excitation threshold of the neurons in the hidden-layer. The MLP with random timing pulses (3) has a pulse oscillation in the excitation threshold of the neurons in the hidden-layer, and this pulse is generated at random. The MLP with pulse glial chain (4) has a glial pulse in the excitation threshold of the neurons in the hidden-layer. In this model, the excitation threshold of glia is constant value. The pulse generation pattern becomes periodic when the output of the neuron is converged by the learning. The neuron-glia network including random glia pulse generation (5) is the proposed network. We use a

Two-Spiral Problem (TSP) for a task of the networks. The TSP is a famous task for the artificial neural network and has a high nonlinearity [11][12]. In this task, the network learns the classification of two dimensions coordinates of two spirals. The learning spiral points is shown in Fig. 3.

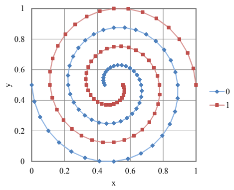

Fig. 3. Target points.

We obtain the experimental results from 100 trials about each MLP. In each trial, we give the different initial weights of connections. The MLP has 50000 iterations during one trial and learns 130 data sets of spiral points. We use the three layers MLP, and the number of neurons in each layer is 2-40-1. We use Mean Square Error (MSE) for the error function. The MSE is described by Eq. (6).

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

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

We show the accuracy of the classification to the learning data set. The learning performance of networks is shown in Table I. The standard MLP (1) is the worst of all in the average error, the minimum error and the maximum error. We can say that the standard MLP (1) falls into local minimum. The MLP with random noise (2) and the MLP with random timing pulse (3) reduce the error than the standard MLP (1), however these methods do not have a large difference from the standard MLP (1). On the other hand, the MLP with pulse glial chain (4) and the proposed network (5) decrease the error more than others. The maximum error of proposed network is smaller than the MLP with pulse glial chain (4). In the case of the MLP with pulse glial chain (4), the pulse generation pattern becomes periodically toward the end of learning. The randomly oscillation of glia excitation threshold changes the pulse generation pattern toward the end of learning; thus the pulse gives the more energy to the network

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)	0.11439	0.00740	0.26349	0.05742
(4)	0.01990	0.00067	0.11664	0.02226
(5)	0.01436	0.00069	0.08139	0.01688

IV. CONCLUSION

In this study, we have proposed the artificial neuron-glia network including random glia pulse generation. The glias are one-by-one connected with the neurons in the hidden-layer. The glia generates the pulse according to the connecting neuron output. This pulse transmits to the neighboring glias and the neurons. In the proposed model, the glia has the randomly oscillation in the excitation threshold. The pulse generation becomes randomly toward the end of learning by the randomly oscillation of glia excitation threshold. The random pulse generation is efficiency to the network learning. We confirmed that the proposed MLP has the better performance than the conventional MLPs.

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