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Multi-Layer Perceptron with Pulse Glial Chain

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Abstract—A glia is a nervous cell in the brain. Currently, the glia is known as a important cell for the human's cerebration. Because the glia transmits signals to neurons and other glias. We notice features of the glia and consider to apply it for an artificial neural network.

In this paper, we propose a Multi-layer perceptron (MLP) with pulse glial chain. The pulse glial chain is inspired from the features of the glia. The glia generates a pulse by a connecting neuron and it excites neighborhood neurons and glias. The pulse is generated as different glia, thus, these pulses look like propagating into the network. We show the MLP with pulse glial chain has better performance than the conventional MLP by computer simulations.

1. Introduction

A glia is one of the nervous cell which is existing in a brain. The glia was known to supporting cell for neuron works by carrying a nutrient for a long time. Recently, some researchers discovered that this cell had high calcium response capability, and that the calcium response was provoked by the glutamic acid [1][2]. The glutamic acid is an important ion in the brain, because this ion is one of a neurotransmitter as a synapse. Thus, the glia is known to be actively involved with information processing of the brain.

We have noticed the biological glia works in the brain and considered that apply this work to the artificial neural network. We used a Multi-Layer Perceptron (MLP) for one of the applying model [3]. The MLP is the most famous feed forward neural network. It is known to solve the pattern recognition, pattern classification, data mining and so on. The MLP is composed by some neurons, and the neurons compose some layer. These neurons connect neighborhood layer's neurons. The MLP is learned by Back Propagation (BP) [4]. The network become to solve linearly-inseparable problem, however, the BP algorithm often falls into local minimum. Because, the BP uses the steepest decent method. If the MLP can escape out from the local minimum, this network find a better solution.

In this study, we propose a MLP with pulse glial chain. A pattern of glia firing looks like a pulse. The glia is fired by connecting neuron output. If the one glia is fired, around glias are fired chain reaction. In our proposed glial chain, the glia generates the pulse output by the connecting neuron's huge output, after that the other glia is excited chain reaction. We confirm by computer simulations that the glial chain improves the learning performance of the MLP by connecting the neurons more effectively than the conventional networks.

2. MLP with pulse glial chain

The MLP is one of the feed forward neural network and is composed by some neuron layers. The MLP is learned by BP algorithm from the network error. This network can solve many kinds of tasks, for example, pattern recognition, pattern classification, data mining and so on. In this study, our MLP has three layers (which is composed by 4–10–1) and hidden layer neurons have the glial chain shown in Fig. 1.

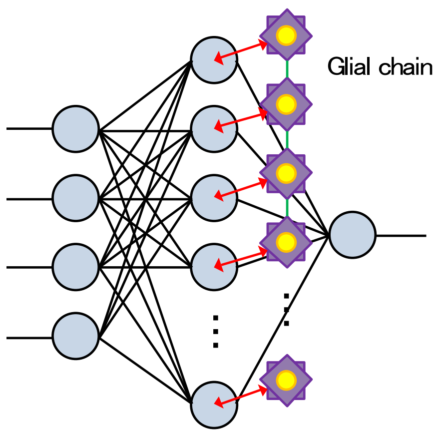


Figure 1: MLP with pulse glial chain.

2.1. Neuron updating rule

The neuron has multi-inputs and one output. We can process the neuron output by the deciding weight parameter between neurons. The standard neuron updating rule is described by Eq. (1).

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

where y is a neuron output, x is an input from forward layer neurons, w is a weight parameter, θ is a threshold and f is an output function. The weight parameter and the threshold are learned by BP algorithm.

The updating rule of the hidden layer's neurons of the proposed neural network with the glial chain is modified as Eq. (2).

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

where ψ : output of the glias, α : weight of glia outputs. We use the sigmoid function for the output f as Eq. (3).

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

2.2. Glial network

Currently, the glia is attract researchers attentions in the biological or the medical fields. Because, the glia has important work for brain system. The glia has many kinds of ion receptors. Especially, the glia change Ca^{2+} density in the brain and this calcium response likes pulse response [5][6]. The Ca^{2+} affect to the neuron membrane potential. Moreover, the glia's calcium response occur chain reaction as around glias [7][8].

In this study, we propose the pulse glial chain which is inspired from these features of glia. The pulse glial chain is generated by the glias. One glia generates pulse output and the pulse is propagating in the glial chain. We define that only one glia (first glia as the glial chain) is excited by the neuron output, after that other glia is excited by this glia's pulse output. Thereby, the glia's pulse output looks like propagating other glia passing into the glial chain. The pulse output of first glia is defined in Eq. (4).

$$\psi_1(t+1) = \begin{cases} 1, & (\theta_n < y_1) \cap (\theta_g > \psi_1(t)) \\ \gamma\psi_1(t), & else, \end{cases} \quad (4)$$

where ψ is the glia pulse output, γ is an attenuated parameter, θ_n is a threshold of the exciting glia and θ_g is a threshold of a glia's refractory period. Other glias have different conditions of exciting. These glias are excited by first glia output. If the first glia is excited by neuron output, this information is propagating into the glial chain. After that, other glias excite and generate the pulse output. These glias' exciting conditions are defined in Eq. (5).

$$\psi_i(t+1) = \begin{cases} 1, & (\theta_t < \psi_1(t - i * D)) \cap (\theta_g > \psi_i(t)) \\ \gamma\psi_i(t), & else, \end{cases} \quad (5)$$

where D is number of delay and θ_t is a threshold of first glia output. Figure 2 is an example of the glia generating pulse. In this figure, the pulse conditions are $\gamma = 0.8$, $\theta_n = 0.8^{45}$, $\theta_n < y_1$ (every time) and $D = 1$. The first glia generates pulses by neuron output. The pulses excite neighborhood glia, thereby, the pulse looks like propagating into the glial chain. One glia output is decreased at an exponential rate and if the glia is excited, it can not excite during period of inactivity.

Next, we show the pulse outputs when the glias do not have the relationship of each other for in Fig. 3. Each pulse detail is the same as the pulse of Fig. 2. However, in these pulse outputs, they are independent from other glias, thus the pulse outputs are generated at different times as each position of glia. We confirm that the relationship of the glias is important for the MLP learning by comparing the MLPs which are connected glias of two different conditions of the generating pulse outputs.

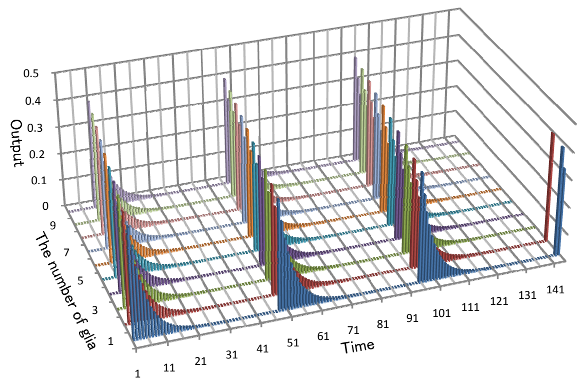


Figure 2: Propagating pulse by the pulse glial chain (D = 1)

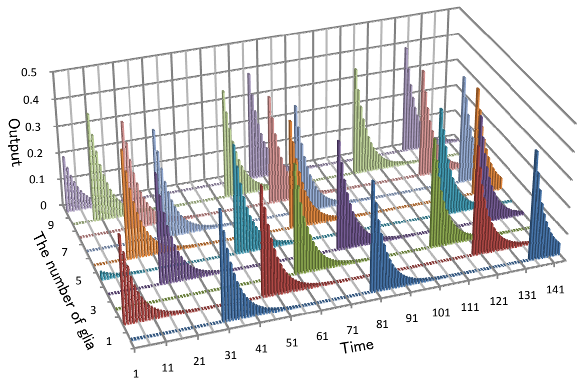


Figure 3: Generating the pulse at random timing.

3. Simulations

In this section, we confirm the efficiency of the glial chain to the learning performance of the MLPs. We compare the four kinds of MLPs, which are

(1) Conventional MLP

(2) MLP with pulse glial chain ($D = 1$)

(3) MLP with pulse glial chain ($D = 0$)

(4) MLP with random timing pulse.

3.1. Simulation task

In this simulation, the MLP learns classification of two skew tent maps. The skew tent map generates the chaotic time series and the MLP learns time change. The skew tent map is described by Eq. (6).

$$\phi_i(t+1) = \begin{cases} \frac{2\phi(t)+1-A}{1+A} & (-1 \leq \phi(t) \leq A) \\ \frac{-2\phi(t)+1+A}{1-A} & (A < \phi(t) \leq 1) \end{cases}, \quad (6)$$

where ϕ is a chaotic oscillation as each time and A is feature of the skew tent map. If A is changed, the skew tent map has different oscillations. In the skew tent map, the chaotic time series change between -1 and 1. The neuron inputs value are between 0 and 1. Thus, we normalize the chaotic time series by skew tent map to between 0 and 1. Figure 4 is a map of the skew tent map as the two different A.

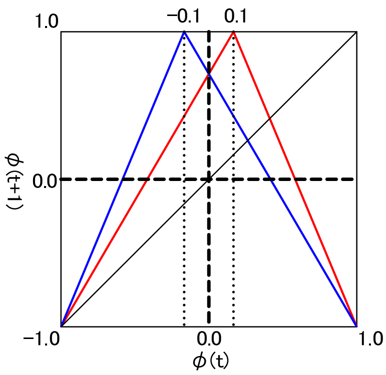
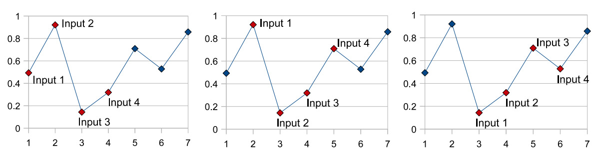


Figure 4: Skew tent map.

The BP learning for the MLPs is carried out by giving four successive points of the chaotic time series as an input and the following 0 or 1 as an output. The learning is repeated for 200 different sets which are included two different chaotic time series like Fig. 5.



(a) Step 1. (b) Step 2. (c) Step 3.

Figure 5: Learning procedure.

3.2. Simulation results

First, we show statistic results which are an average of error (Avg.), a minimum error as 200 trials (Min.), a maximum error as 200 trials and a standard deviation of errors in Table 1. The MLPs learn chaotic time series of different initial conditions. As one trial, the MLPs learn during 50000 times, after that we check the each index. We obtain the statistic results from 200 trials. From this result, we can see that the MLP with the pulse glial chain is the best result of all as every index. In the conventional MLP, the learning performance is the worst, because this network often falls into local minimum during learning. The average of error of the MLP with pulse glial chain ($D = 0$) is worse than the MLP with pulse glial chain ($D = 1$). We consider this reason that this MLP ($D = 0$) is given too much energy from the pulse glial chain. Because the neurons in this MLP, are given pulses as same time, thus, the MLP has large error and learns different points.

Table 1: Learning performance.

	Avg. Err.	Min.	Max.	St. Dev.
(1)	0.0029	0.0001	0.0605	0.0079
(2)	0.0008	0.0001	0.0202	0.0022
(3)	0.0017	0.0001	0.0209	0.0037
(4)	0.0012	0.0001	0.0603	0.0048

Next, we show the learning curve of the MLPs. We can see that the MLP with pulse glial chain ($D = 1$) has the best learning performance, and that the conventional MLP and the MLP with chain glial chain ($D = 0$) converged early and can not reduce the error. We consider that the conventional MLP and the MLP with pulse glial chain ($D = 1$) are trapped local minimum. Comparing results, the MLP with pulse glial chain ($D = 1$) can escape out from the local minimum.

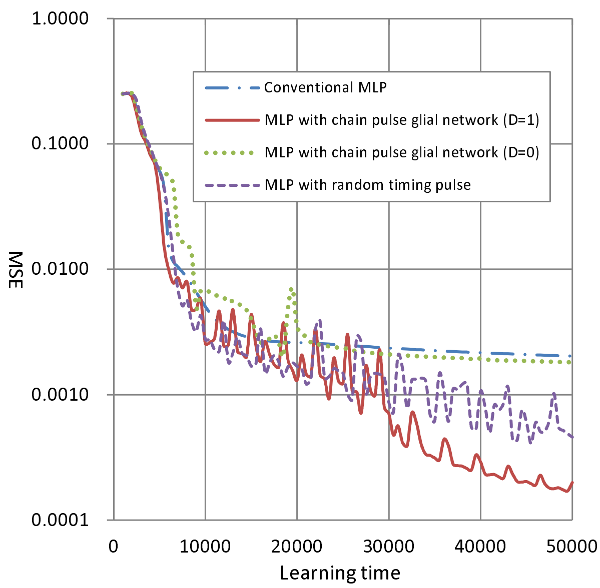


Figure 6: Learning curves by the MLPs.

3.3. Parameters dependency

Finally, we show that the parameters dependency of the MLP with pulse glial chain. We change the number of delay D and the weight of glia output α. Figure 7 is the average of error by 100 trials as each condition. From this figure, the error is small when D are 1 and 9. We consider that the MLP need above a certain energy for escaping out from the local minimum. In $D = 1$, the MLP is given large energy, because, the glial chain generates pulse as very similar timing. And also, in $D = 9$, the MLP is given large energy by three glias, because, the pulse is delayed as propagating into the glial chain, and the first glia generates next pulse, which is shown in Fig. 8.

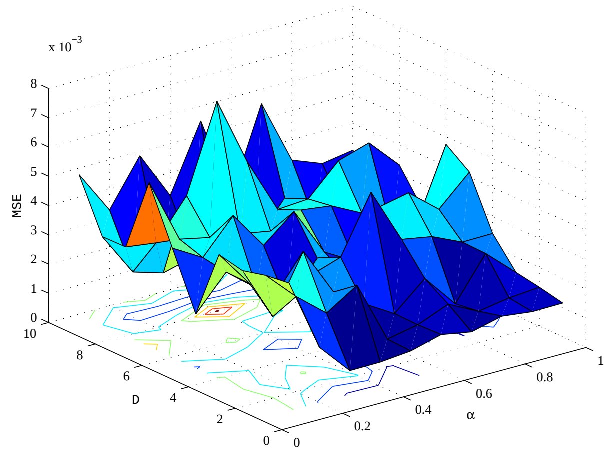


Figure 7: Parameter dependency of the pulse glial chain.

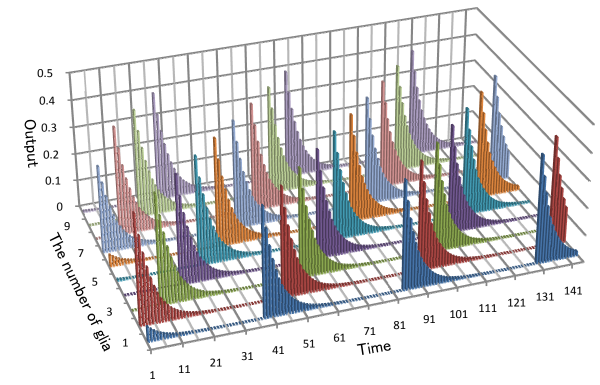


Figure 8: Propagating pulse by the pulse glial chain as (D = 9).

4. Conclusion

In this study, we have proposed the MLP with pulse glial chain. This MLP is inspired from the biological nervous systems. In the pulse glial chain, the first glia generates pulse output exciting by the connecting neuron output. The first glia's pulse output excites neighborhood glia, after that the neighborhood glia generates similar patter pulse and this process is continued. Thus, the pulse looks like propagating into the glial chain.

The MLP with pulse glial chain is better than the conventional MLP for learning the chaotic time series. Because the MLP with pulse glial chain has the pulse by the glia, it is helped that the MLP escaped from the local minimum. After that we researched the parameter dependency of our MLP. In this result, we found two characteristic parameters which are $D = 1$ and $D = 9$. We consider that the MLP can be obtained above a certain energy by the glial chain. Because the pulses are generated at similar timing as these conditions.

Acknowledgment

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