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Multi-Layer Perceptron with Impulse Glial Network

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***Abstract*— We have proposed the glial network which was inspired from the feature of brain. In the glial network, glias generate independent oscillations and these oscillations propagated neurons and other glias. We confirmed that the glial network improved the learning performance of the Multi-Layer Perceptron (MLP)**

In this article, we investigate the MLP with the impulse glial network. The glias have only impulse output, however they make the complex output by correlating with each other. The simulation result shows that the proposed networks possess better learning performance than the conventional MLP.

I. Introduction

The artificial neural network is a brain's neurons model which is variously applied, the neural network was inspired from behavior of the biological neurons. In the brain, the neural network manages much information by the signal transmitting of neurons. The Multi-Layer Perceptron (MLP) is one of feed forward neural networks and is useful to perform several tasks, for example, pattern recognition, pattern classification, data mining and so on. Back Propagation (BP) algorithm is a learning algorithm for the MLP using the steepest decent method [1].

We have proposed the glial networks to improve the performance of MLP. The glial network was inspired from the feature of the glias which are existing in the brain. Recently, some researchers discovered that the glias transmit signals by using ions [2]. In the brain, the glias influence each other and the ions affect neurons' thresholds [3][4]. We tried to exploit the glia network's behavior such that another network located close to the neural network helps the functions of the neural networks. In [5], we proposed the MLP with the glial network whose glias generated independent oscillations and these oscillations propagated neurons and other glias. We confirmed by computer simulations that the glial network improved the learning performance of the MLP by connecting the neurons more effectively than the conventional networks.

In this paper, we propose a MLP with the impulse glial network. In this network, all glias generate impulses when the glia is excited by the connecting neuron. The glia connects the neuron and watch to neuron's output. If the neuron's output becomes to high, the glia generates an impulse. After that, this impulse is propagating in the glial network, this glia can not generate the impulse during constant time like biological neuron's refractory period. We consider that all glias generate the impulses at random times each other, the glias' effects give good influence to the MLP.

II. MLP with Impulse Glial Network

The MLP is the most famous feed forward neural network. Several methods using the MLP has been proposed for solving many kinds of tasks. This network has some neuron layers and the weights between the layers are learned by the BP algorithm. In this study, we use the MLP with three layers (4-10-1) and a glial network connected to the hidden layer.

A. Neuron Updating Rule

The standard neuron updating rule is given by Eq. (1).

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

where x : input or output, w : weight parameter, θ : threshold and f : output function. The parameters w and θ are learned by using the BP algorithm.

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

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

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

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

B. Impulse Glial Network

In the biological neural network, it is known that the glias affect the neighboring neurons over a wide range by making their outputs to be propagated in the network. The output of the glias can be given as Eq. (4).

$$\Psi_i(t) = \sum_{k=-m}^{m} \beta^{|k|}\psi_{i+k}(t-|k|), \quad (4)$$

where ψ is the glia making impulse, β denotes attenuation parameter and m is propagating range of glia's impulse. We defined the glia's impulse, it is given by Eq. (5).

$$\begin{aligned} \psi_i(t+1) &= 1, \quad (\theta_n < O_i) \cap (\theta_g > \psi_i(t)) \\ \psi_i(t+1) &= \beta\psi_i(t), \quad else, \end{aligned} \quad (5)$$

where θ_n is a threshold of existing the glia, O is an output of each neuron and θ_g is threshold of glia's refractory period.

The glia generates the impulse output as exiting by neuron's output. However, if neuron's output is not over threshold or into the refractory period, the glia can not generate the impulse and this glia's output is attenuated by β.

III. Simulation Results

In this section, we show the performance of the proposed MLP with the impulse glial network by learning two kinds of chaotic time series. We use the skew tent map as different A to generate chaotic time series. The skew tent map is formulated by Eq. (6).

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

Figure 1 is skew tent map which is given by Eq. (6).

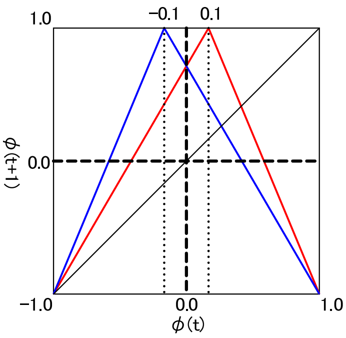


Fig. 1. Skew tent map ($A = -0.10, 0.10$).

The skew tent map generates chaotic time series between -1 and 1, thus, we linear transform chaotic time series which become between 0 and 1. The MLP learns to two different chaotic time series of classification. If the MLP takes $A = -0.10$ chaotic time series, the MLP learns to 1 and if the MLP takes $A = 0.10$ chaotic time series, the MLP learns to 0. Figure 2 shows example of learning chaotic time series.

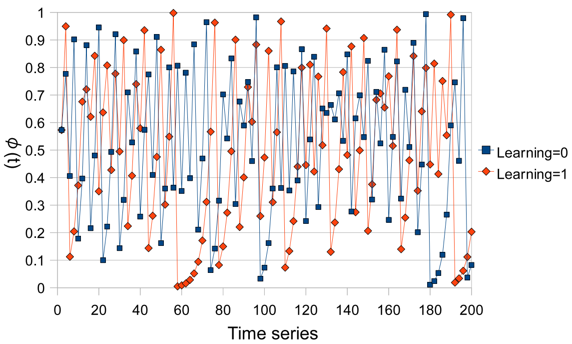
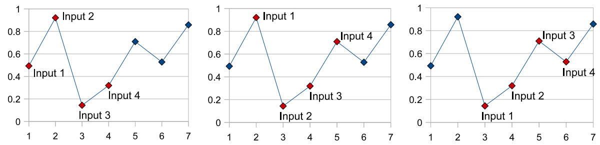


Fig. 2. Chaotic time series ($A = -0.1,\ 0.1$).

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. 3.



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

Fig. 3. Learning procedure.

We compare the performances of four different MLPs, which are the conventional MLP, the MLP with the impulse glial network, the MLP with the glial network and the MLP with inputted random noise. We use the following Mean Square Error (MSE) for evaluate these performances.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - O_i)^2, \tag{7}$$

where N is the number of trials and t is a target value.

We investigate the learning performance of the MLPs by calculating the time evolution of the errors. The number of the trials is 100 and the MLPs learn 25000 times during one trial. We calculate the average of error (Avg. Err.), the minimum error (Min.), the maximum error (Max.) and the standard deviation (St. Dev.). Table I shows the obtained results.

TABLE I

Learning performance.

	Avg. Err.	Min.	Max.	St. Dev.
Conventional	0.0351	0.0011	0.1179	0.0434
Impulse Glia	0.0053	0.0005	0.0615	0.0068
Glia	0.0074	0.0016	0.0644	0.0125
Noise	0.0111	0.0009	0.1098	0.0190

In the average of error, we can see that the conventional method is the worst. The MLP with the impulse glial network and the MLP with the glial network reduce more the maximum error than the conventional MLP and the MLP with inputted random noise. We consider that the MLP with glial networks could escape out from the largest local minimum, on the other hand, they could not escape from it.

Figure 4 shows an example of the learning curves. The error of the conventional MLP converges constant value and is not improved any more. The learning curve of the MLP with the impulse glial network has some small peak, we consider that the part of glias are synchronized, thus, the impulse glial network give large influences to the MLP learning, and this oscillations become a good influence to the MLP.

IV. Conclusion

In this article, we have proposed the MLP with the impulse glial network. The glias generate impulse output by the MLP's output, moreover the outputs are propagating to other glias, thus the glial network can generate complex oscillations. We could see that the glias' outputs were sometimes synchronized as local positions in the impulse glial network.

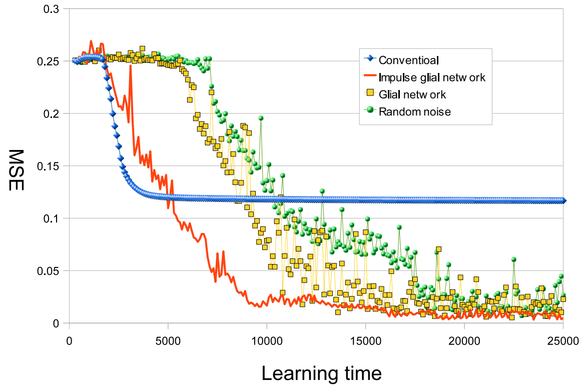


Fig. 4. Error curve of four different MLPs.

By computer simulations, we confirmed that the proposed MLPs with the impulse glial networks is better learning performance. The impulse glial network has state of synchronization and getting out synchronization, thus, the network can make large outputs and small outputs. We consider that this behavior gave good influence to the MLP learning.

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