1-25

Multi-Layer Perceptron Including Learning-Neuron Chosen by Regularly-Firing-Glia

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1. Introduction

A glia is a nervous cell existing in a brain. This cell has not been investigated, because it can not use an electric signal similar to a neuron. However, some researchers discovered that the glia uses various ions concentration to signals [1]. Among them, we have focused attention on functions of Ca^{2+}. The glia generates the Ca^{2+} concentration wave. The synapse long-term potentiation is controlled by increasing the Ca^{2+} concentration, moreover the Ca^{2+} concentration wave is propagated to wide range. Thus, the glia has a significant influence on the neuron learning.

In this study, we propose a Multi-Layer Perceptron (MLP) including leaning-neuron chosen by regularly-firing-glia. The hidden-layer neurons are separated to some groups. Each group alternately changes between a learning term and a non-learning term. During the learning term, the neurons in the same group are learned by Back Propagation (BP) algorithm. On the other term, the weight of connection between the input-layer and the hidden-layer is not updated. By computer simulation, we confirm the performance of the proposed MLP.

2. Proposed method

The MLP is a famous feed forward neural network. This network is composed of layers of neurons. The MLP generally learns by the BP algorithm. However, the MLP has the local minimum problem, because the BP uses the steepest decent method. For the local minimum problem, we often add a noise to any part of the MLP.

In this study, we propose the MLP including learning-neuron chosen by regularly-firing-glia. In the proposed MLP, the hidden-layer neurons are separated to some groups according to the connected glias as shown in Fig. 1. The glias fire with regularity. The weights of connections of neurons which are connected with the firing glia are updated. For the other neurons, their weights between the hidden-layer and the output-layer are updated, however their weights between the input-layer and the hidden-layer are not updated. We use the standard BP to the updating rule of weight of connections. The updating weight is described in Eq. (1).

$$\Delta w = -\eta \frac{\partial E}{\partial w}, \quad (1)$$

where w is the weight of connection, η is a learning coefficient, and E is an error of the MLP.

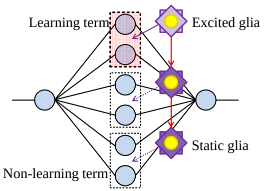
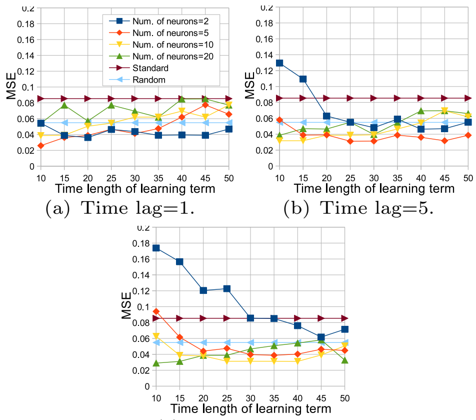


Figure 1: Proposed MLP.

3. Simulation

Two-spiral problem is a famous benchmark for the artificial neural network. It is known as a high nonlinearity problem. In this benchmark, the MLP are inputted the coordinates of two different spirals and learns its classifications. After learning, the MLP classifies the unknown coordinates to either one of the two-spiral.

In this simulation, neurons in each layer are composed of 2-40-1. The iterations are 100000. The error index is the Mean Square Error (MSE). We compare the learning performance of the proposed MLP with the standard MLP and MLP with random noise. Moreover, we investigate the performance when we change the number of neurons for one group, the time length of the learning term, and time lag of the learning term.



(a) Time lag=1.　(b) Time lag=5.
(c) Time lag=10.

Figure 2: Approximation results.

From Fig. 2, the performance of the proposed MLP is better than the standard MLP and the MLP with random noise when we choose the suitable conditions. We can see that the number of neurons for one group contradict the time length of the learning term. From this result, we confirm that the performance of the proposed MLP can be tuned by changing the parameters.

4. Conclusions

In this study, we have proposed the MLP including learning-neuron chosen by regularly-firing-glias. The hidden-layer neurons are separated to some group according to the glias. The neurons are changed between the learning term and the non-learning term with regularity. At the learning term, the neurons are learned. On the other term, the weight of connection between the input-layer and the hidden-layer is not updated. Two terms impinge on MLP learning like a noise. By the simulation, we showed that the changing two terms improved the MLP performance. Moreover, we confirmed characteristics of the proposed MLP.

References

[1] P.G. Haydon, "Glia: Listening and Talking to the Synapse," *Nature Reviews Neuroscience*, vol. 2, pp. 844-847, 2001.