

# Investigate of Multi-Layer Perceptron with Neurogenesis

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## 1. Introduction

Neurogenesis is that new neurons are generated in the human brain. By utilizing the neurogenesis, some brain cells increase and the network of within is substantial. The neurogenesis causes the improvement of memory, learning, thinking ability, and so on by generation new neurons with biological neural network.

In this study, we apply the behavior of neurogenesis to the artificial neural network. In the proposed neural network, we use the Multi-Layer Perceptron (MLP) which is one of a feed-forward neural network. In order to confirm the efficiency of neurogenesis, we investigate the performance of MLP with neurogenesis for learning several alphabet patterns.

## 2. Proposed Network

MLP is a most famous feed-forward neural network. In this study, we use the Back Propagation (BP). We consider that the proposed network is composed the three-layers (one input, one hidden, and one output layer) MLP. In the proposed neural network, some new neurons are generated in a hidden layer during the learning process. We consider a pattern recognition, where 26 alphabets patterns are fed the neural network for recognition. Figure 1 shows a structure of the proposed MLP. We used the input patterns of alphabets A to Z as shown in Fig. 2.

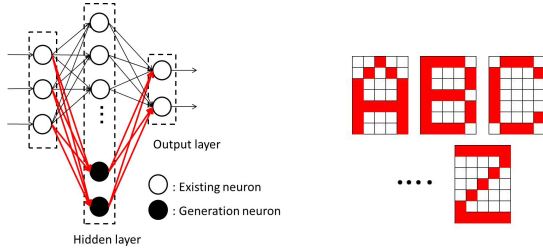


Figure 1: Proposed network. Figure 2: Input patterns.

The updating rule of neuron and the sigmoid function are described by Eqs. (1) and (2).

$$x_i(t+1) = f\left(\sum_j w_{ij}(t)x_j(t) - \theta\right), \quad (1)$$

$$f(a) = \frac{1}{1 + e^{-a}}, \quad (2)$$

where  $x$  is the input or output and  $w$  is the connection weight parameter and  $\theta$  is threshold.

The total error  $E$  of the network is described by Eq. (3).

$$E = \frac{1}{2} \sum_{p=1}^p \sum_{i=1}^n (t_{pi} - o_{pi})^2, \quad (3)$$

where  $E$  is the error value,  $p$  is the number of the input data,  $n$  is the number of the neurons in the output layer,  $t_{pi}$  is the value of the desired target data for the  $p$ th input data, and  $o_{pi}$  is the value of the output data for the  $p$ th input data. The connection weight is described by Eq. (4).

$$\Delta_p w_{ij}^{k-1,k} = \eta_{pj}^k o_{pi}^{k-1} = -\eta \frac{\partial E_p}{\partial w_{i,j}^{k-1,k}}, \quad (4)$$

where  $w_{i,j}^{k-1,k}$  is the weight between the  $i$ th neuron of the layer  $k-1$  and the  $j$ th neuron of the layer  $k$ , and  $\eta$  is the proportionality factor known as the learning rate.

## 3. Simulation Results

In this study, we consider a pattern recognition, where 26 alphabets patterns are set the input patterns. The number of neurons in the input layer and output layer are 35 and 26. Similarly, we set 10 neurons in the hidden layer at the start of learning. The number of neurons in the hidden layer is increased from 20 to 60 during the learning. The learning time is set to  $m = 5000$ . The learning rate is  $\eta = 0.005$ , and initial value of the weight are given between -0.5 and 0.5 at random. Moreover, we compare the learning performance of five kinds MLPs:

1. The conventional MLP
2. The MLP with random neurogenesis
3. The MLP with periodic neurogenesis
4. The MLP with intermittency chaotic neurogenesis
5. The MLP with chaotic neurogenesis

The periodic neurogenesis generates the new neuron at every 50 iteration during the learning process. In the case of chaotic neurogenesis, the new neuron is generated by using the logistic map.

We show an example of the learning performance of the MLPs in Fig. 3. In this example, the proposed MLPs are set that the number of neurons in the hidden layer is increased from 10 to 40 neurons during the learning.

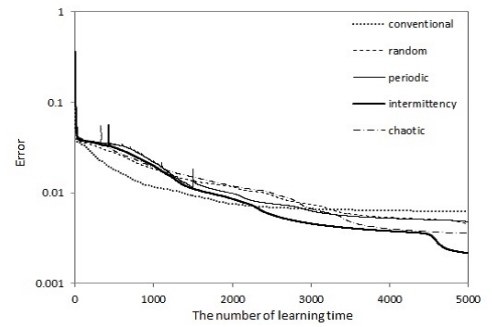


Figure 3: Learning performance of each MLP.

From Fig. 3, we can see that the learning performance of the proposed MLPs are better than the conventional network. We consider that it was able to slip out of the local minima by increasing some neurons during the learning.

## 4. Conclusions

In this study, we applied the behavior of neurogenesis to the MLP. In the proposed neural network, some new neurons were generated in a hidden layer by effect of neurogenesis. We proposed 4 timing methods to introduce neurogenesis. The proposed MLPs were able to obtained the good results for the learning performance by the introducing the neurogenesis.