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Improvement of Learning Performance of Neural Network Using Neurogenesis

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Abstract

Neurogenesis is that new neurons are generated in the human brain. The new neurons create new network. The neurogenesis causes the improvement of memory, learning, thinking ability, and so on. We consider that the neurogenesis can be applied to an artificial neural network.

In this study, we propose the Recurrent Neural Network (RNN) with neurogenesis and apply to pattern learning. In the RNN with neurogenesis, some neurons are replaced with regenerated neurons. We compare the learning performance of the RNN with neurogenesis with the conventional RNN.

1. Introduction

In the human brain, neurons had been considered to be lost with age until several years ago. However, in recent studies, some researchers reported that new neurons are generated in the dentate gyrus of hippocumpus [1][2]. This process is called "neurogenesis". It is reported that this process occur all human brains. It is known that the neurogenesis improves memory and thinking ability by connection of new neurons.

In this study, we apply the behavior of neurogenesis to the Recurrent Neural Network (RNN) which is an artificial neural network. The composed neurons of the RNN have self-feedback and are connected asymmetrically [3]-[5]. Namely, we can say that the property of the RNN structure is similar to the biological neural network.

In the proposed neural network, some existing neurons are replaced to new neurons by effect of neurogenesis. We name this network "RNN with neurogenesis." In order to confirm the efficiency of neurogenesis, we investigate the performance of RNN with neurogenesis for learning several alphabet patterns. By using learning method of Back Propagation Through Time (BPTT), we confirm that the RNN with neurogenesis obtains better results than the conventional RNN.

2. Back propagation Through Time (BPTT)

A Back Propagation Through Time (BPTT) is used to the RNN's learning method [6][7]. The BPTT was introduced by R.J. Williams and D. Zipser in 1989 [8]. The BPTT algorithm is based on the standard BP algorithm of feed-forward neural network. Figure 1 shows the point of view of the BPTT. Figure 1 (a) shows the example of the RNN which is composed of 3 neurons with 2 input. It is possible to replace the network of Fig. 1 (a) on the network of Fig. 1 (b). Figure 2 shows the diagram of error propagation of real time BPTT.

The updating rule of neuron is described by Eq. (1).

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

where f is the sigmoid function, x is the input or the output and w is the connection weight. The sigmoid function is described by Eq. (2). This is used for the output function.

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

Moreover, the complementary error function and the conditional equation are described by Eqs. (3), (4) and (5).

$$J(t_l,t) = -\frac{1}{2}\sum_{\tau=t_l+1}^{t}\sum_i e_i(\tau)^2, \tag{3}$$

$$e_i(t) = \begin{cases} d_i(t)-x_i(t) & if \quad i\in O \\ 0 & otherwise, \end{cases} \tag{4}$$

$$t_l = t-\alpha. \tag{5}$$

where d is the teaching signal, O is the set of output unit, t_l is the time to initialize network state using new patterns and α

is the time between the input layer and the output layer. The updating type of connection weight is described by Eqs. (6) and (7).

$$\Delta w_{ij} \quad = \quad \eta \sum_{\tau=t_l}^{t-1} \delta_i(\tau+1) x_i(\tau), \qquad (6)$$

$$\begin{cases} \delta_i(t) = f'(s_i(t)) e_i(t) \\ \delta_i(\tau) = f'(s_i(\tau))(e_i(\tau) + \sum_j w_{ji} \delta_j(\tau - 1) \\ \qquad\qquad\qquad\qquad if \;\; \tau < (t-1), \end{cases} \qquad (7)$$

where η is the learning rate, δ is the back propagation term, s_i is the internal state and τ is the time constant.

Figure 3 shows explanation of ITERATION and EPOCH. We define ITERATION and EPOCH to use the BPTT algorithm. ITERATION is the number of learning of one pattern in EPOCH. EPOCH is the number of patterns and ITERATION.

3. RNN with Neurogenesis

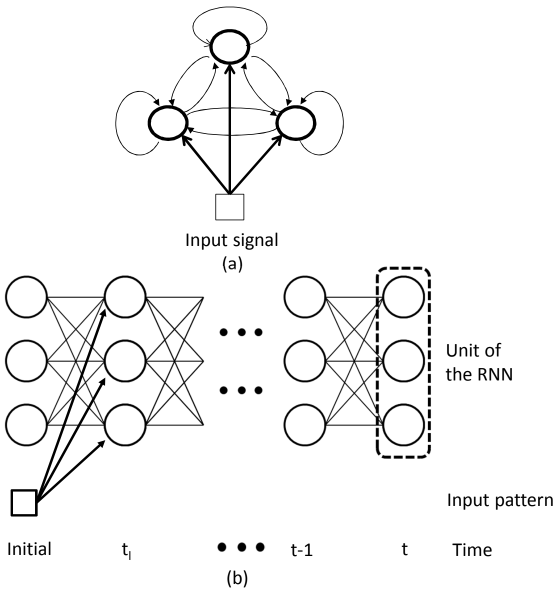

Figure 1: The composition of the RNN for the BPTT logic.

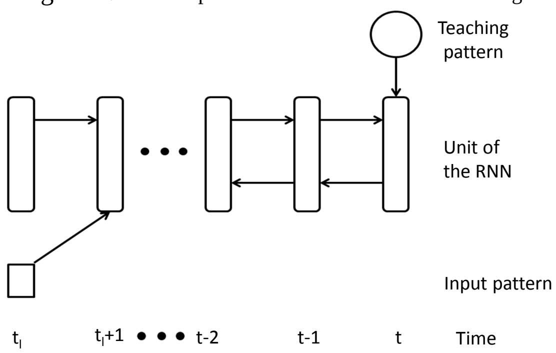

Figure 2: The BPTT algorithm.

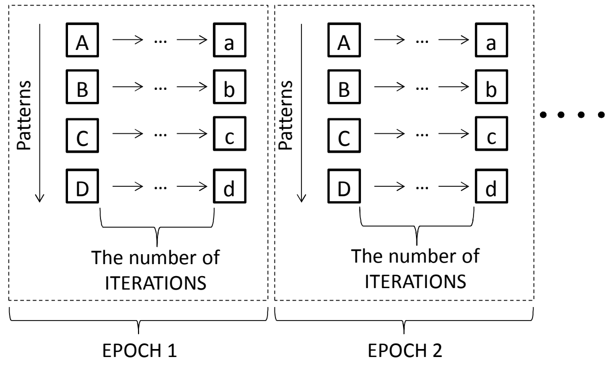

Figure 3: Explanation of ITERATION and EPOCH.

The neurogenesis in the hippocumpus of the human brain was discovered in the late 1990s by Erickson et al. Before that time, the neurons had been considered to be lost with age. The neurogenesis is that new neurons are regenerated in the human brain. The neurogenesis causes to improve memory, learning, thinking ability, and so on. We believe that to adapt the neurogenesis to the RNN can be effective for improve learning performance, and propose the RNN with neurogenesis.

We explain the RNN with neurogenesis. Figure 4 shows a structure of the RNN with neurogenesis. In this system, existing neurons are randomly chosen and removed, and then new neurons are regenerated to the removed neurons. At the same time, all the weights connecting to the regenerated neurons are newly set between -0.5 and 0.5 at random. In this study, the process to regenerate neurons and connection is "neurogenesis." After that, the connection weights are newly calculated.

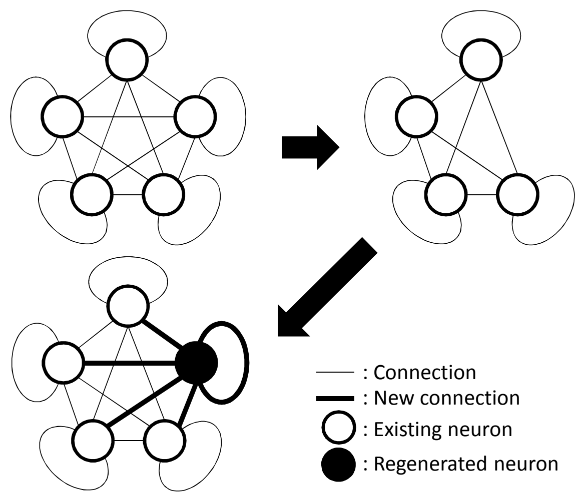

Figure 4: The model of the RNN with neurogenesisn.

4. Simulation Results

In this study, we consider the RNN with 100 neurons. The time between the input layer and the output layer is $\alpha = 10$. We make a comparison between the performance of the conventional RNN and the proposed the RNN with neurogenesis. Figure 5 shows input patterns and teaching patterns. In this study, we prepare 4 learning patterns. We randomly compose 100 each network and calculate average of the number of agreement between output patterns and teaching patterns. Here, if different value of corresponding position between output patterns and teaching patterns is less than 0.2, we consider as agreement. We examine the performance of the conventional RNN and the RNN with neurogenesis using two simulations.

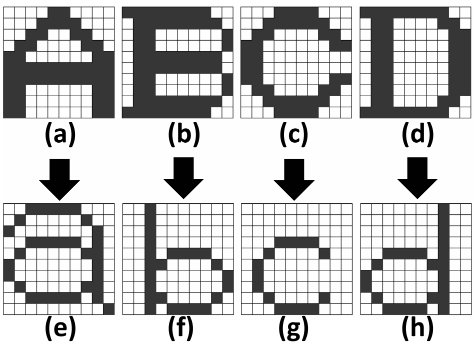

Figure 5: Learning patterns. (a)-(d) Input patterns. (e)-(h) Teaching patterns.

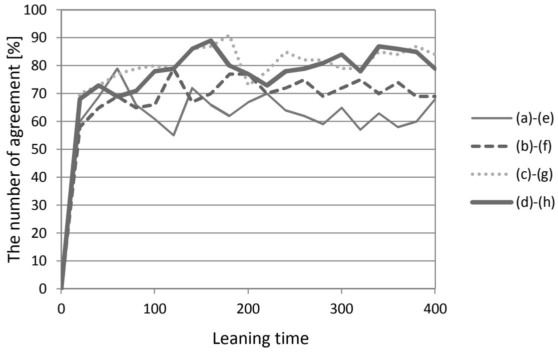

Figure 6: The simulation results of the conventional RNN (average : 75.0%).

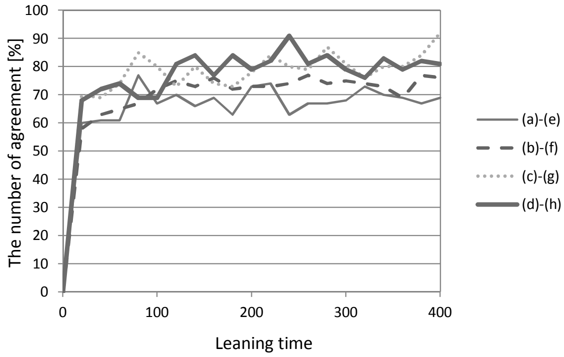

Figure 7: The simulation results of the RNN with neurogenesis (average : 79.5%).

4.1. Influence by the Neurogenesis

In this simulation, we show that the neurogenesis has an influence on the network. The number of learning times is 400, EPOCH is 20 and ITERATION is 20. We introduce the 10 regenerated neurons by 2 steps till EPOCH 18. The RNN and the RNN with neurogenesis learn each pattern.

Figure 6 shows the performance of the conventional RNN. And, Fig. 7 shows the performance of the RNN with neurogenesis. From these results, the performance of the RNN with neurogenesis is difference from the RNN. Therefore, we can say that the neurogenesis is had influence on the RNN.

4.2. The Performance of the RNN with Neurogenesis

In this simulation, we examine the performance of the RNN with neurogenesis depending on the number of the regenerated neurons and the timing of set of regenerated neurons. The number of learning times is 200, EPOCH is 10 and ITERATION is 20. The RNN and the RNN with neurogenesis learn 4 learning patterns. Table 1 shows the performance of the RNN with neurogenesis if the number of regenerated neurons increases by 10 or the regenerated neurons are set at EPOCH 2, 4, 6, and 8. And Fig. 8 is visualization of Tab. 1.

Table 1: Performance of the RNN. (A) The number of regeneration neurons. (B) The number of agreement.

Network type	(A)	(B) [%]			
		Timing			
		2	4	6	8
Conventional	0	70.60	70.60	70.60	70.60
RNN with neurogenesis	10	**72.16**	71.33	71.55	71.31
	20	71.96	71.19	70.89	70.30
	30	71.66	70.28	70.72	69.61
	40	71.49	71.09	70.88	70.10
	50	71.99	70.47	70.36	70.26
	60	**72.48**	69.69	70.94	69.14
	70	71.59	70.72	69.82	68.68
	80	70.81	70.01	70.76	68.35
	90	71.22	69.59	70.61	68.48
	100	71.56	70.11	69.75	67.91

From these results, we consider that the performance of the RNN with neurogenesis is better than the conventional RNN in a certain case. Especially, we can say two things.

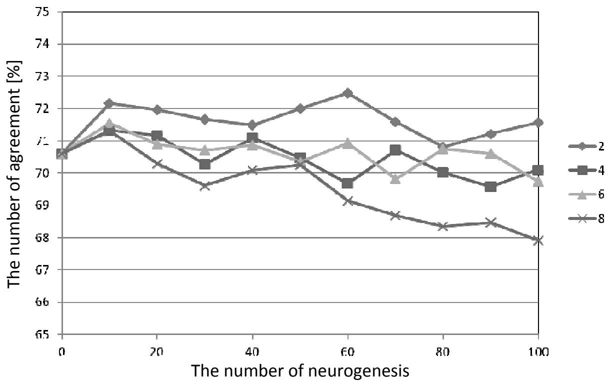

Figure 8: The simulation results.

First, even if the timing of set of the regenerated neurons is changed, the performance of the RNN with neurogenesis is better than the conventional RNN for the number of the regenerated neurons 10. In this instance, the best performance is 72.16% . This value improved about 2.0% as many as the conventional RNN. Second, even if the number of the regenerated neurons is changed, the performance of the RNN with neurogenesis is better than the conventional RNN for the timing of set of the regenerated neurons 2. In this instance, the best performance is 72.48% . This value improved about 2.5% as many as the conventional RNN.

Therefore, if the timing of set of the regenerated neurons or the number of regenerated neurons exceed a certain value, it is very highly possible that the performance of the RNN with neurogenesis is less than the conventional RNN. Namely, in this study, we can assume that the optimal number of the regenerated neurons to achieve the best performance of the RNN with neurogenesis exists.

5. Conclusion

In this study, we applied the behavior of neurogenesis to the Recurrent Neural Network (RNN) which is an artificial neural network. The composed neurons of the RNN have self-feedback and are connected asymmetrically. Namely, we can say that the property of the RNN structure is similar to the biological neural network.

In the proposed neural network, some existing neurons are replaced to new neurons by effect of neurogenesis. We named this network “RNN with neurogenesis.” In order to confirm the efficiency of neurogenesis, we investigated the performance of RNN with neurogenesis for learning several alphabet patterns. By using learning method of Back Propagation Through Time (BPTT), we confirmed that the RNN with neurogenesis obtains better results than the conventional RNN.

Acknowledgment

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