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Improvement of Neural Network Learning Performance by Resting and Working State

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Abstract

Currently, many researchers research about relationships of a rest to a work in a field of biomechanical science. Because taking the rests improve efficiency of our works. In fact, we sometime decrease our concentration power by hard works. Then, we must take a rest, because we become tired by a same work for a long time. However, if we take too much rest, the work efficiency is decreased. We should consider the balance between the rest and the work.

In this study, we propose a Multi-Layer Perceptron with Resting State (RSMLP). The RSMLP has two different states, one of the state is a resting state, on the other state is a working state. By computer simulations, we confirm that the RSMLP has better performance than the conventional MLP and the MLP with random noise by learning a step function.

1. Introduction

Back Propagation (BP) was proposed by D. J. Rumelhart in 1987 [1]. The BP algorithm is used for learning of several artificial neural networks. In this algorithm, the network calculate the error from the output and learning points. After that, this error is propagating backward in the network. The network can learn to tasks by the repeating this process. However, the BP algorithm often falls into the local minimum, because this algorithm uses the steepest descend method. In order to avoid this problem, we propose a new scheme for this algorithm.

Currently, many researchers research about relationships of a rest to a work in field of biomechanical science. Because taking the rests improve efficiency of our works. In fact, we sometime decrease our concentration power by hard works. Then, we must take a rest, because we become tired by a same work for a long time. In general, we can refresh by taking the short time rest. Some research groups have reported that our works grow in efficiency by taking appropriate amount of the rests [2]-[4]. However, if we take too much rest, our work efficiency is decreased. We should consider the balance between the rest and the work.

In this study, we propose a Multi-Layer Perceptron with Resting State (RSMLP). The RSMLP has two different states, one of the state is a resting state, on the other state is a working state. The RSMLP changes the two states during the learning process and learn to tasks. The working state is the standard BP learning. In the resting state, the RSMLP cuts the input of learning task and continues the learning. We expect that the RSMLP obtains a good performance by repeating the working and the resting states. We confirm that the RSMLP has better performance than the conventional MLP by learning a step function. Furthermore, we investigate the performance of the RSMLP when the ratio between the working and the resting states is changed.

2. MLP with Resting State

A Multi-Layer Percetron (MLP) is one of a feed forward neural network. The MLP is known to be able to solve some kinds of tasks, for example, the pattern recognition, the pattern classification, the data maiming and so on [5][6]. This network is composed of some neuron's layers and learns to the tasks by changing the weight parameters. The performance of the MLP is changed by the number of neurons and the number of layers.

In this study, we consider that the RSMLP is composed of three layers (connected 1-5-1). The updating rule of neuron is given by Eq. (1).

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

where x: input or output, w: weight parameter and θ: threshold. We use sigmoidal function for output function as Eq. (2).

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

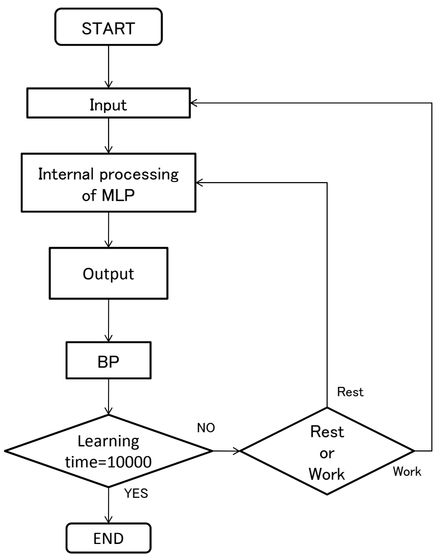

Figure 1: Flow chart of RSMLP.

We show a flow chart of the learning process using the RSMLP in Fig. 1. The RSMLP has two different states during the learning process. One of the state is the working state which is learned by the BP in the same way as the conventional method. On the other hand, it is the resting state. During the resting state, the RSMLP is cut the input which is learning task, moreover, we give the random oscillation to the RSMLP's input. The two states are changed periodically. The neuron updating in the input layer of the resting state is defined as Eq. (3).

$$x_i(t+1) = f(\psi), \tag{3}$$

where ψ is the random oscillation as the noise.

3. Simulation Results

We compare the learning performance of the RSMLP, the conventional MLP and the MLP with a random noise (which is given random oscillation to neurons' threshold) by learning a step function as shown in Fig. 2. The MLPs learn to each point of vertical axis's value from the input value (horizontal axis's value).

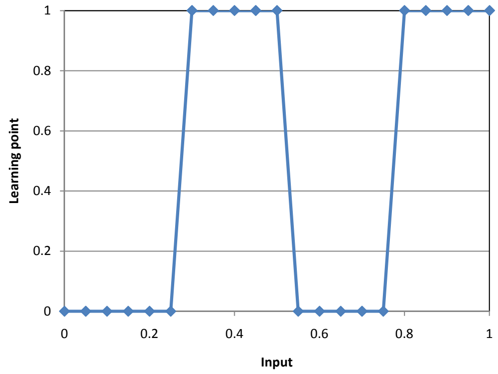

Figure 2: Step function.

We use Mean Square Error (MSE) as the error function. The MSE is given by Eq. (4).

$$MSE = \frac{1}{N}\sum_{i}^{N}(t_i - O_i)^2, \tag{4}$$

where t_i is learning point, O_i is the MLP's output and N is the number of learning points.

3.1. Performance of RSMLP as Different Ratio of Rest to Work

First, we compare the learning ability of the RSMLP by changing the ratio of the working state and the resting state. We change the time span of the working state and the resting state little by little. The MLPs learn to the 21 point and the iteration time is fixed as 10000. Table 1 shows the simulation results of the average MSE when the ratio of the working and the resting states is changed. We obtain the average MSE of 100 trials by changing the initial condition.

Table 1: Performance of the RSMLP as different ratio of the rest to the work. (a) is the span of the resting state. (b) is the span of the working state.

		(b)					
		100	200	400	600	800	1000
(a)	10	0.004	0.004	0.003	0.004	0.006	0.009
	20	0.030	0.004	0.005	0.004	0.006	0.004
	40	0.119	0.034	0.008	0.005	0.005	0.005
	60	0.152	0.057	0.017	0.011	0.006	0.005
	80	0.157	0.067	0.030	0.014	0.010	0.007
	100	0.160	0.100	0.034	0.019	0.009	0.007

In Tab. 1, the errors of the upper triangular matrix are smaller than the errors of the lower triangular matrix. Thus, the learning performance of the RSMLP becomes worse when the ratio of the resting state to the working state becomes high. Moreover, the error of the upper right in Tab. 1 is worst than around the center of Tab. 1. We consider that the MLP should be taken the enough rest, however, too much rest gives bad influence to the learning ability of the RSMLP.

Figure 3 shows the relationship between the ratio of the resting state to the working state and the error. We can see that if the ratio of resting state become high, the error increase exponentially. The error is the smallest value when the ratio of the resting state is fixed from 0.02 to 0.1. Thus, we should choose the appropriate ratio of the resting state to obtain the good learning ability.

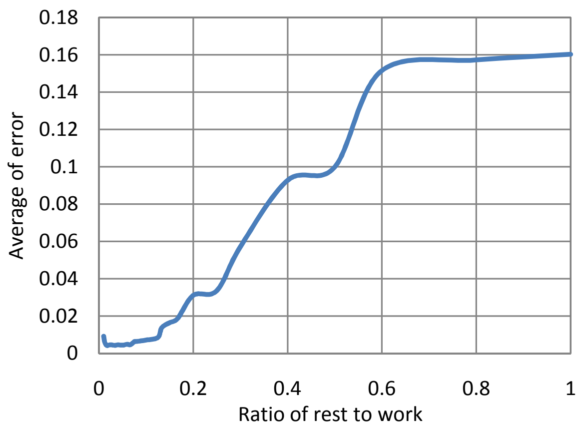

Figure 3: Average of error as each ratio of resting and working.

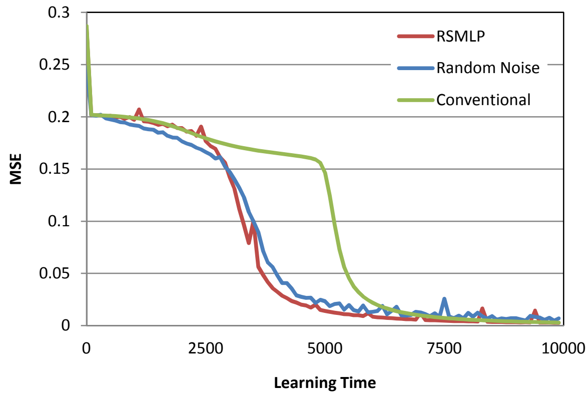

Figure 4: Learning curve of each MLP.

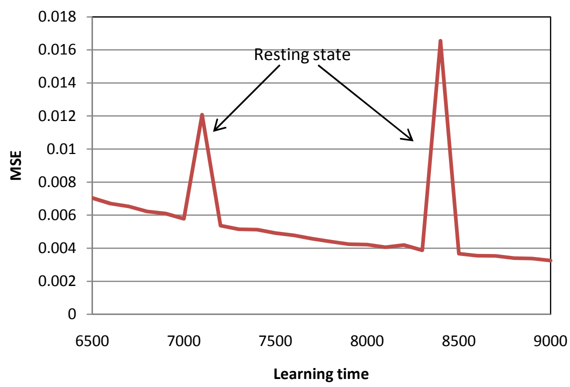

Figure 5: Learning curve of RSMLP as the local time.

3.2. Performance of the MLPs

Next, we compare the learning performance of the three kinds of MLPs which are the RSMLP, the conventional MLP and the MLP with the random noise.

Figure 4 is an example of the error curves of the MLPs. We can see that every MLP can reduce the error to around 0. However, the RSMLP and the MLP with the random noise reduce error earlier than the conventional MLP. In general, solution searching performance of the MLP becomes high by adding the noise. We consider that the RSMLP has similar ability to the MLP with the random noise.

In Fig. 4, the learning curve of the RSMLP converges smooth. Actually, the RSMLP is learned to false data during the resting state. We show the scale up learning curve as $ratio = 0.1$ in Fig. 5. From this figure, we can see that the resting state has the certain period of time. The error of the RSMLP becomes large at the resting state, however, the error is decreased more at the next working state.

Table 2 shows the average of the error (Avg. Err.), the minimum error (Min.) and the maximum error (Max.)) of the 100 trials. We used the RSMLP as the ratio to 0.1 for comparing performance of the MLPs. From Tab. 2, the RSMLP is the best of all for the average of the error and the maximum error. We consider that the RSMLP could reduce the influence of the local minima from the maximum error to be became small value by repeating the resting and the working states.

Finally, we show the recalling of the learning point by using the three MLPs in Fig. 6. We plot the learning data and the output data of the MLPs after learning process. In this result, the recalling point of the conventional MLP is as same as the recalling point of the MLP with random noise. They could not learn enough to the learning data. In the RSMLP, the recalling result was similar to the learning data than the others. Thus, we consider that the resting state can give good influence to the MLP learning.

Table 2: Performance of the MLPs

	Ave. Err.	Min.	Max.
RSMLP (Ratio=0.1)	0.00360	0.00244	0.01191
Random noise	0.00764	0.00164	0.17249
Conventional	0.00988	0.00177	0.17321

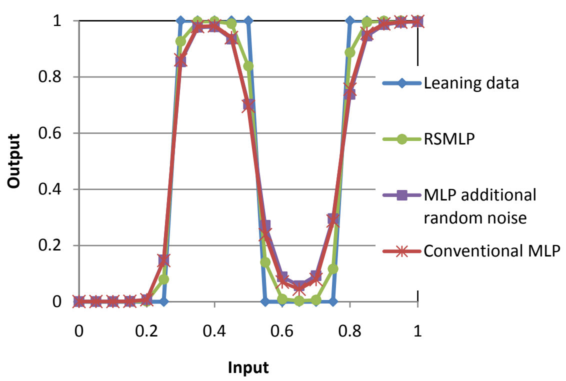

Figure 6: Recalling step function by MLPs.

4. Conclusion

In this study, we have proposed MLP with the resting state. The RSMLP has two different states which are the resting state and the working state. During the working state, the RSMLP learned by standard BP algorithm. While, in the case of the resting state, the input data was cut. The two states were switched during the learning process.

By computer simulations, we confirmed that the RSMLP was better than the conventional MLP and the MLP with random noise when the ratio of the resting state to the working state was small. If the ratio of the resting state and the working state was large, the learning ability of RSMLP became worse. Further, we showed the result of pattern recalling by the RSMLP and the recalling result was close to the learning data. Thus, we consider that the resting state can give good influence to the MLP learning.

References

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