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# Investigation of Neural Network Repeating Two Kinds of Sleeps

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## 1. Introduction

In general, a sleep is important for the human's life. Human repeats two kinds of sleeps which are Rapid Eye Movement sleep (REM sleep) and Non Rapid Eye Movement sleep (non-REM sleep). During the REM sleep, the brain is waking and eyes usually move. On the other hand, the brain takes deep rest during the non-REM sleep. These two states are important for ordinary brain function.

In this study, we propose the Multi-Layer Perceptron (MLP) with repeating REM sleep and non-REM sleep. In the proposed MLP, the learning data are inputted with adding random noise during the REM sleep. On the other hand, the learning data are not inputted to the MLP at all during the non-REM sleep but only the random noise is inputted. We show the propose MLP has better learning performance than the conventional MLP by the simulation.

## 2. REM and non-REM sleeps

The proposed MLP has a waking part, the REM sleep part, and the non-REM sleep part. In the waking part, the proposed MLP learns true learning data. After while, the MLP makes the shift to the sleep part. First, the MLP goes into the non-REM sleep. During the non-REM sleep, the input connections are cut and random noise are inputted to the neurons on the input layer. After that, the MLP goes into the REM sleep. In this sleep part, the learning data with adding noise are inputted to the neurons on the input layer. The MLP makes the shift to the waking state after repeating the two sleeping states several times.

In this simulation, the neuron updating rule is described by Eq. (1).

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

which $y$ is an output, $f$ is sigmoidal function, $w$ is a weight parameter, $x$ is an input, and $\theta$ is a threshold. In the sleep part, the neuron updating rule of input layer changes. In the case of the non-REM sleep, the neuron updating rule of the input layer is given by Eq. (2).

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

where $\phi$ is a uniformed random noise. In the REM sleep, it is given by Eq. (3).

$$y_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)\{(x_j(t)\phi(t)\} - \theta_i(t)\right). \quad (3)$$

## 3. Simulation

In this simulation, we use the three layer's MLP which is composed (1–5–1). The MLP learns a step function. We obtain learning result from the 100 trials. We define that the ratio of between the waking part and the sleep part is 2 : 1. In the sleep part, the ratio of between the non-REM sleep and REM sleep is 2 : 1. Moreover, the non-REM sleep and the REM sleep are repeated 6 times during one sleeping. These conditions are similar to the ratio in real human. First we show the statistic results on Table 1. From this table, the proposed MLP has a better learning performance than the other MLPs. Moreover, we can see that the two kinds of sleep parts improve the MLP learning performance.

Table 1: Learning performance.

| | Avg. Err. | Min. | Max. |
|---|---|---|---|
| Conventional | 0.0434 | 0.0006 | 0.1486 |
| Proposed | 0.0085 | 0.0070 | 0.1491 |
| Only non-REM | 0.0264 | 0.0163 | 0.1541 |
| Only REM | 0.0519 | 0.0007 | 0.1474 |

Next, we show an example of the learning curves of the MLPs in Fig. 1. From this figure, we can say that the proposed MLP converges earlier than the others. In the case of only non-REM sleep, the leaning curve makes oscillations. Because the random noise is given to the i

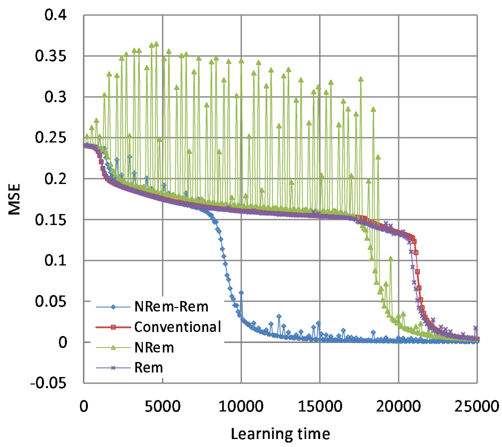


Figure 1: Example of learning curves.

## 4. Conclusions

In this study, we have proposed the MLP with repeating the REM sleep and the non-REM sleep. The proposed MLP has two kinds of sleep parts. We confirmed that the two kinds of sleep parts improve the learning performance of the MLP.