Outstanding pattern discrimination ability of spatiotemporal learning rule

Yota Tsukamoto, Hiromichi Tsukada, Minoru Tsukada, and Tohru Ikeguchi

Among the most well-known learning rules to achieve synaptic plasticity is the Hebbian learning rule[1], which modifies synaptic weight according to both activity of presynaptic neurons and that of postsynaptic neurons. However, Tsukada et al. identified long-term potentiation induced only by activity of presynaptic neurons[2]. The spatiotemporal learning rule (STLR), which causes this phenomenon, differs from the Hebbian learning rule in that activity of postsynaptic neurons has nothing to do with long-term potentiation. Then, STLR has proven to excel at pattern discrimination, or distinguishing similar input patterns, compared with the Hebbian learning rule[3, 4]. However, STLR has yet to be analyzed in detail.

In this paper, we simulated pattern discrimination by the Hebbian learning rule, the Hebbian± learning rule, and STLR[3]. The neural network of interest comprises N formal neurons. Its connectivity is single-layered and feed-forward. The firing of the i-th postsynaptic neuron at discrete time t_n, which is expressed as $y_i(t_n)$, is determined by the following equation[4]:

$$y_i(t_n) = \begin{cases} 1 & s_i(t_n) \geq \eta \\ 0 & s_i(t_n) < \eta, \end{cases} \tag{1}$$

where η is the threshold of firing and $s_i(t_n)$ is the membrane potential, which is expressed as follows:

$$s_i(t_n) = \sum_{j=1}^{N} w_{ij}(t_n) x_j(t_n), \tag{2}$$

where $x_j(t_n)$ is the firing of the j-th presynaptic neuron and $w_{ij}(t_n)$ is the synaptic weight connecting the i-th postsynaptic neuron and the j-th presynaptic neuron. $x_j(t_n)$ and $y_i(t_n)$ take either "1" (action potential) or "0" (resting potential).

STLR modifies synaptic weight by the following equation:

$$w_{ij}(t_{n+1}) = \begin{cases} w_{ij}(t_n) + \Delta w, & J_{ij}(t_n) \geq \theta_1 \\ w_{ij}(t_n), & \theta_2 < J_{ij}(t_n) < \theta_1 \\ w_{ij}(t_n) - \Delta w, & J_{ij}(t_n) \leq \theta_2, \end{cases} \tag{3}$$

where Δw is the learning rate, and θ_1 and θ_2 are threshold of long-term potentiation and long-term depression, respectively. The temporal history of spatial coincidence, $J_{ij}(t_n)$, is defined as Eq.(4):

$$J_{ij}(t_n) = \sum_{m=0}^{n} I_{ij}(t_m) \exp\left(-\frac{t_n - t_m}{\lambda}\right), \tag{4}$$

where λ is the time constant and $I_{ij}(t_n)$ is the spatial coincidence expressed as follows:

$$I_{ij}(t_n) = w_{ij}(t_n) x_j(t_n) \sum_{k=1, k \neq j}^{N} w_{ik}(t_n) x_k(t_n). \tag{5}$$

In the learning process, five input patterns are applied to the neural network at discrete time $(t_1, \ldots, t_5)$. After learning completes, one of the five input patterns is given and an output pattern is obtained. We repeated the above-mentioned procedure for all the permutation of input patterns ($5! = 120$) and evaluated the pattern discrimination ability. As a result, the Hebbian learning rule and the Hebbian± learning rule failed to distinguish the order of the given patterns. On the contrary, STLR showed that appropriate parameters achieve outstanding pattern discrimination ability.

The research of H. T. was partially supported by JSPS KAKENHI Grant Number JP20H04246. The research of T. I. was partially supported by JSPS KAKENHI Grant Numbers JP20H00596, JP21H03514, and JP22K18419.

References

[1] D. O. Hebb, The organization of behavior: A neuropsychological theory, Oxford: Wiley, 1949.

[2] M. Tsukada et al., *Neural Networks*, 9(8), 1357–1365, 1996.

[3] M. Tsukada and X. Pan, *Biological Cybernetics*, 92(2), 139–146, 2005.

[4] H. Tsukada and M. Tsukada, *Frontiers in Systems Neuroscience*, 15, 624353, 2021.