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Research article

Learning Times Required to Identify the Stimulated Position and Shortening of Propagation Path by Hebb's Rule in Neural Network

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Abstract: To deepen the understanding of the human brain, many researchers have created a new way of analyzing neural data. In many previous studies, researchers have examined neural networks from a macroscopic point of view, based on neuronal firing patterns. On the contrary, we have studied neural networks locally, in order to understand their communication strategies. To understand information processing in the brain, we simulated the firing activities of neural networks in a 9 × 9 two-dimensional neural network to analyze spike behavior. In this research study, we used two kinds of learning processes. As the main learning process, we implemented the learning process to identify the stimulated position. As the subsidiary one, we implemented Hebb's learning rule which changes weight between neurons. Three channels with transmission and reception were preset, each of which has a different distance and direction. When all three channels succeeded in identifying the source stimulation in the receiving neuron group, it was regarded as an overall success and the learning was termed as successful. Furthermore, in order to see the effect of the second learning procedure, we elucidated the average of necessary learning times in each channel type and compared the firing

propagation time of the first trial and an overall successful trial, in each channel. We found that the firing path after learning is shorter than the firing path before learning. Therefore, we deduced that Hebb's rule contributes to shortening the firing path. Thus, Hebb's rule contributes to speeding up communication in a neuronal network.

Keywords: spike wave; Hebb's rule; learning times; firing propagation times; neural network

1. Introduction

The brain is a large network system that transmits information through spikes. Spikes are short electrical signals in neurons that from the substrate of the action potential, which transfers information from the presynaptic neuron to the postsynaptic neuron with a time delay. Information processing in the brain is performed using spike propagation. Despite fluctuations in spike timing, information processing in the brain is relatively stable. As a result, several research studies focus on elucidating the mechanisms of spike propagation and information transmission. The first theory of the learning process in the brain is the cell-assembly theory proposed by Hebb [1,2]. This theory was based on previous findings in associative memory and cell assembly. Okada *et al.* [3] examined the relationship between associative memory and sparse coding. The second theory involves the synfire chain model proposed by Abel [4,5]. This theory states that neuronal groups fire in a synchronous time pattern. However, the transfer of information between neurons and the function of such communication has not been fully elucidated. One such unanswered question is how neural activity propagates through cortical networks that are connected through synapses [6]. Tanaka *et al.* [7] showed that cortical networks use recurrent circuits in which a large number of neurons are bound to each other. For solving information flow, many approaches have been presented, such as path planning using spike wave propagation [8,9], phase-response curves [10,11], spatiotemporal coding models [12,13], and synchronous action models [14,15]. These researches analyze the wave behavior in the neuronal network. However, they don't deal with point-to-point communication itself in the neuronal network.

We proposed a time-shift diagram method in Figure 1, which can be used to visualize the information flow in the brain [16-18]. However, the questions have arisen, for example what constructs the information; how information communication is controlled; and ③ how the controlled information communication is constructed are unanswered. To answer these questions, it is essential to investigate the underlying mechanism of information communication. Therefore, we need to decode the sequence pattern of spike activity (analyses of the time-series of the patterns of firing), rather than examine the rate of spikes or action potential waveforms. In several studies [19-22], we conducted a physiological experiment in cultured neurons from the hippocampus of a rat. In this experiment we observed the generation of a number of spatiotemporal forms of spike wave propagations by various stimulated neurons in a cultural neuronal network.

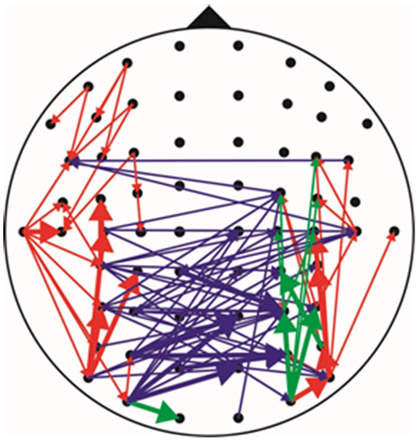

Figure 1. Time-shift diagram of 10.2 Hz magnetoencephalography for a number-counting task [17]. Red arrows with lag time < 5 ms runs within each hemisphere; blue with lag time > 10 ms run across the callosum.

We stimulated one of the two transmission neuron groups, and used the dynamic time warping (DTW) method [23] to determine whether remote neurons can identify the transmission neuronal group that was stimulated [24]. We then confirmed the existence of two types of neurons: those that can identify the stimulated neuron, and those that cannot. However, in that study, we were unable to elucidate the mechanisms underlying these results. Within cultures, parameters such as connection weights and synaptic delays are fixed and cannot be manipulated. Therefore, in order to investigate the effects of synaptic delays and refractory periods, we performed a simulation of spike responses to fluctuating synaptic propagation delays and refractory periods [25]. The simulation was conducted under the condition that the weights of the synapses were all fixed. This was done to examine the effects of fluctuations in the synaptic propagation delays and refractory periods. In order to focus on communication, we analyzed the information-flow of the network. We suggested that variations in synaptic delays and refractory periods would improve the stability of multiplex communication [25]. Similarly, in this study, we simulated the spike response and counted the number of learning times until each communication succeeded in three kinds of stimulations. In addition, we calculated and compared propagation speeds in the first trial and the overall successful trial with three kinds of stimulations.

2. Methods

2.1. Specification of the simulated neural network

A 9 × 9 two-dimensional neural network was implemented, as shown in Figure 2. Computational complexity became bigger if network scale was larger. The aim of this study is to examine only the learning effect, so we set the small networks. We used an integrate-and-fire model without any leakage as the neuronal model [26-28] (sections 2.3 and 2.4) Each neuron had connection weights to and from eight neighboring neurons. We generated random weights of the synapses in the beginning of each trial. Three neurons were simultaneously stimulated at 0.1 ms, as shown in Figure 2. We chose three neurons because we found in a number of preliminary simulations that the stimulation of three or more neurons stabilizes information propagation. We characterized the three neurons as constituents of the stimulated (transmitting) neuron group. Spike waves were propagated from the stimulated neuron group to other neurons. We also assigned three neurons in a receiving-neuron group. The receiving-neuron group receives spikes from the stimulated neuron group. A channel consisted of one stimulation neuron group and one receiving neuron group. We set three channels: stimulated by top (St-T), stimulated by left (St-L), and stimulated by diagonal (St-D), in Figure 2. The spike wave generated from each channel of the stimulated neuron groups arrives at the corresponding receiving neuron group. This study wanted to see the learning effect. So we chose neurons manually. The results of simulations with random neurons, we will present the details in another paper [29].

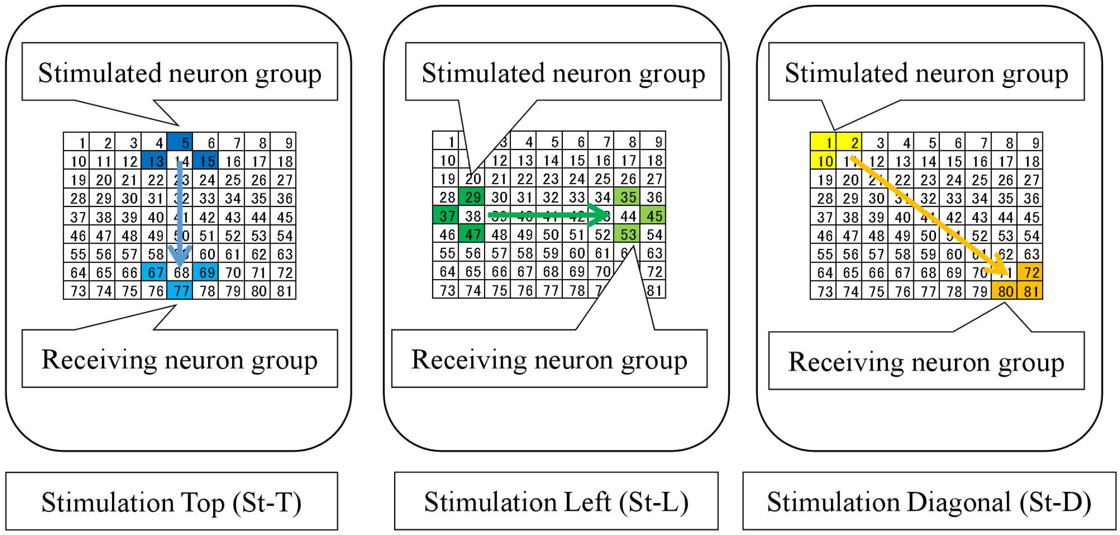

Figure 2. Three channels in a 9×9 simulation. Stimulated by top (St-T): Blue; stimulated by left (St-L): Green; stimulated by diagonal (St-D): Yellow. Arrows in the channels indicate information transmission.

2.2. Simulation trial and the three type stimulations

An example of a trial has been shown below, in Figure 3. Individual training starts from St-T. Neuron group St-T is stimulated at 0.1 ms. A spike train between 0-100 ms after stimulation is observed. We identified the source stimulation in the receiving neuron group, St-T (chapter 2.3), and enhanced the weights among neurons using Hebb's rule (chapter 2.4). Next, individual training of channel L starts. Individual training is repeated in the order of channel T, channel L, and channel D. We have defined this below as the learning cycle. When the individual training of channel D is completed, if all individual trainings were successful for the first time named overall success, the trial will be terminated. Then, the number of trials, named *learning times*, is the output. When the source stimulation identification of even one individual training fails, individual training of channel T will start again. The three channels arranged only in the vertical direction, and only in the horizontal direction were defined as "type V" (vertical), and "type H" (horizontal) respectively, as shown in Figure 4. The three channels arrowed in the vertical, the horizontal, and the diagonal direction were defined as "type M" (mix), as shown in Figure 4. We compared the necessary *learning times* on all types of groups.

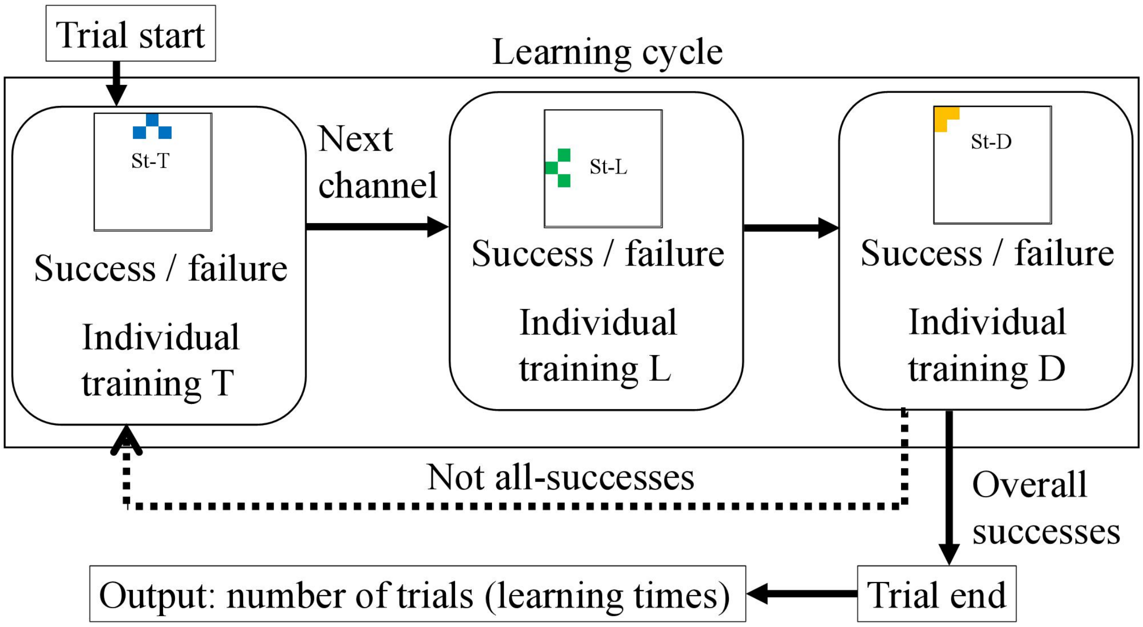

Figure 3. The structure of a simulation trial. Individual training is repeated in the order of channel T, followed by channel L, and channel D. Stimulated by top (St-T): Blue; stimulated by left (St-L): Green; stimulated by diagonal (St-D): Yellow.

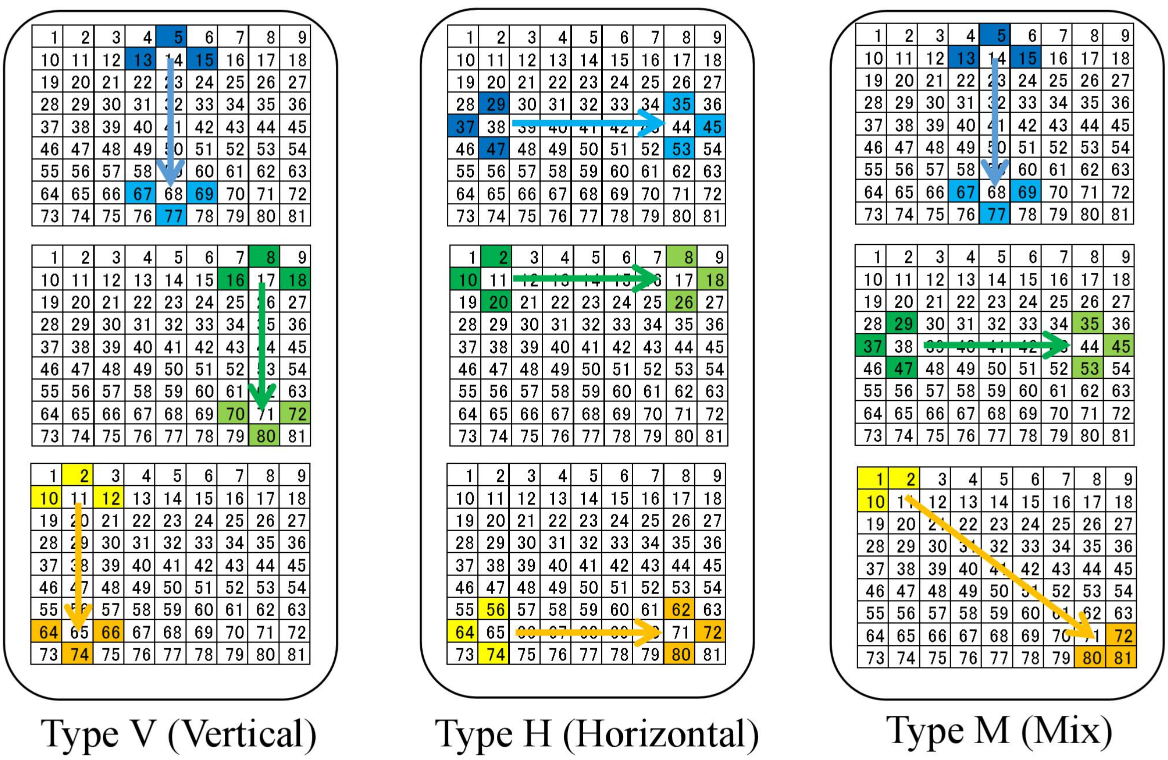

Figure 4. Three-type stimulations. Left: Type vertical; center: Type horizontal; right: Type

mix. Arrows in the channels indicate information transmission. Stimulated by top (St-T): Blue; stimulated by left (St-L): Green; stimulated by diagonal (St-D): Yellow.

The stimulation propagation time of the stimulated neuron group that arrives at the receiving neuron group at each stimulation is hereinafter referred to as the "firing propagation time". We compared the firing propagation times of the first trial and the overall successful trial with three stimulations in type M only. The learning effect may be biased when using type V and type H which have only fixed directional paths. Therefore we tested type M which has various directions.

2.3. Identifying the stimulation source in the receiving neuron group

To evaluate communication ability by spike waves, we set a receiving neuron group similar to the transmitting neuron group. We could identify stimulation sources by leading four waves with back propagation method in reference [28]. 1^{st}-4^{th} spike waves are received at the j-th receiving neuron in the b-th receiving neuron group. Filter output is calculated as the sum of Laplacian Gaussian weights at the received spikes. Filter shape is modified according to the received spike positions as shown by thin blue. We set a task in which each receiving neuron group decides whether the stimulation added to a transmitting neuron group is to itself or not, based on the received spike waves, up to the 4-th wave [28]. The receiving neuron learns and identifies the peak position of the arriving spike train. We defined it as "identification learning". The learning process is performed until the receiving neuron can correctly identify the spike waves from the stimulated neuron group [25]. Details of this process are going to be shown in [29].

2.4. Weight reinforce algorithm between neighboring neurons

Each neuron has an inherent accepting period, a_n, and output delay time, d_n. In Figure 5, Integrate-and-fire model without leakage, with fluctuation in the parameters of neuron "n". We define the weight from neuron i to neuron j as w_{ij}. $\{i_1, i_2, i_3, \cdots i_{N_A}\}$ is a set of surrounding neurons (spikes) that contribute to the firing of neuron j. N_A is any number from 1 to 8. If neuron i contributes to the firing of neuron j, the value of w_{ij} is increased by α. Typically, α = 0.1. The value of w_{ij} constantly is attenuated by some amount (*beta*) over time. Typically, $\beta = \alpha \times 1/400 = 0.00025$. Furthermore, the drift is controlled so that it falls within the range of ± 1. That is, the value of w_{ij} is strengthened if spike from neuron i arrives in neuron j in the accepting period. This change in weight (reinforcement) is made according to Hebb's rule as follows:

$$\begin{gathered} \omega_{isj} \leftarrow \omega_{isj} + \alpha \; \exists s{:}i_s \in \{i_1, i_2, \cdots, i_{N_A}\}, \\ \text{between every bin (0.1 ms)} \;\; \omega_{isj} \leftarrow \omega_{isj} - \beta \end{gathered} \tag{1}$$

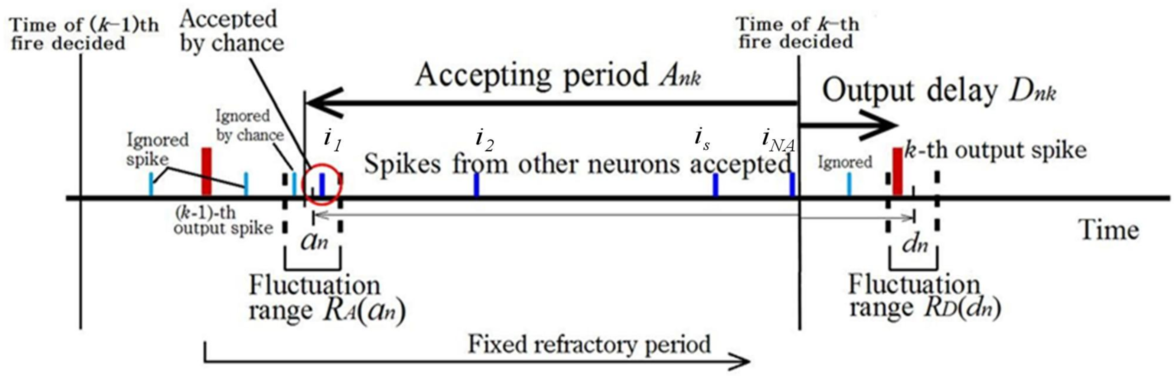

Figure 5. Integrate-and-fire model without leakage, with fluctuation in the parameters of neuron "*n*" [28]. Each neuron has an inherent accepting period, a_n, and output delay time, d_n. Each neuron also has an instantaneous accepting period, A_{nk}, and output delay, D_{nk}, which vary randomly with time within certain ranges defined as $R_A(a_n)$ and $R_D(d_n)$, respectively. At every time point, neuron "n" integrates weighted input spikes during the past accepting period, $A_{nk} \in R_A(a_n)$, for the k-th firing. Then, the neuron determines if the integrated value exceeds zero for firing. If so, the neuron produces a k-th output spike after the delay time, $D_{nk} \in R_D(d_n)$.

3. Results

3.1. Spike propagation

Figure 6 shows the results of a simulation of spike propagation in 9.0 ms. The transmitting neurons were stimulated at 0.0 ms. In all the stimulation patterns (St-T, St-L, and St-D), the spike waves spread in all directions. The propagation route was changed in each trial.

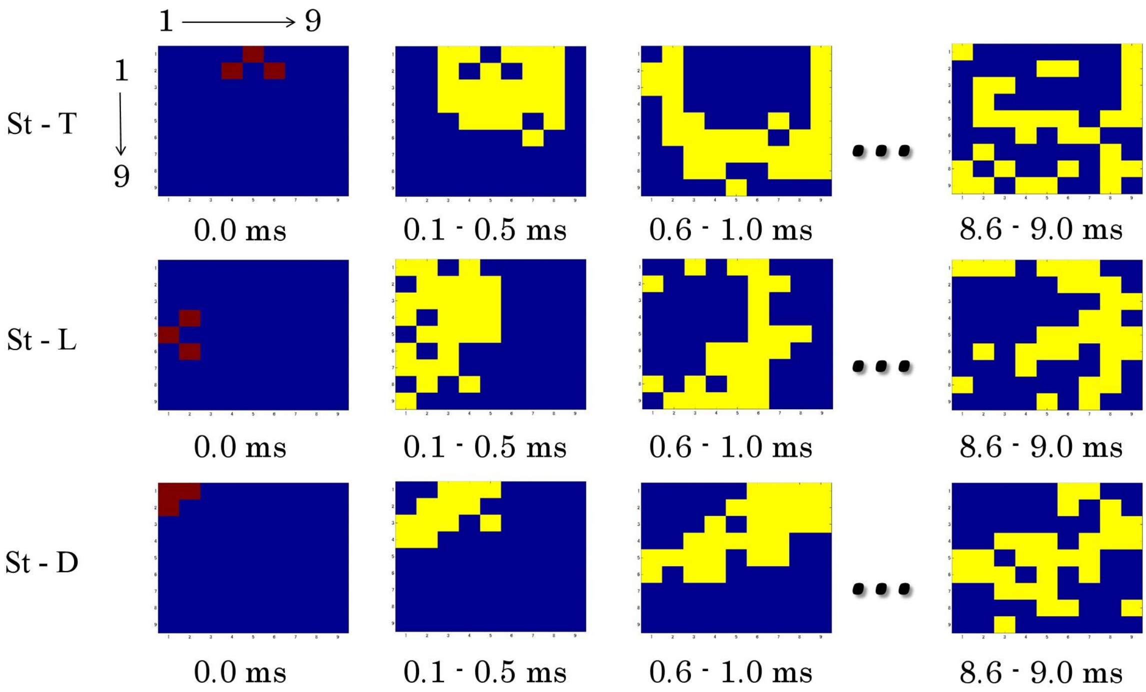

Figure 6. Spike wave of each simulation group. Upper panels: St-T; middle panels: St-L; lower panels: St-D.

3.2. Comparison of necessary trials of the three-type stimulations

Figure 7 shows the average of *learning times* of types V, H, and M that used one-way ANOVA and the Bonferroni method for multiple comparisons. The vertical axis shows the average of trials, and the horizontal axis shows the channel types. The average of learning time in type M was significantly lower than the average of learning times in types V and H.

3.3. Comparison of firing propagation time between the first trail and the overall successful trial in the three channels

In order to ascertain whether the difference between the mean values of the average firing propagation time of St-T (St-L or St-D) at the first trial and the overall successful trial (mean ± SD) is statistically significant, a two-tailed *t*-test was conducted with a significance level of 5%.

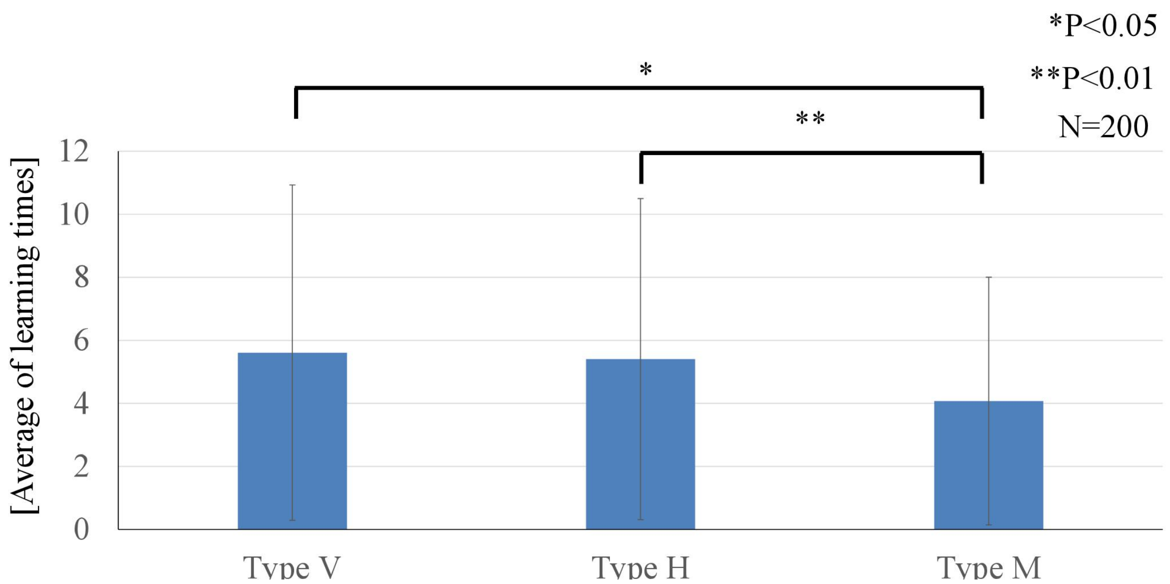

Figure 7. Comparison of necessary learning times of three-type stimulations. **P*<0.05, ***P*<0.01 *vs* type M.

It was found that, the mean value of the average firing propagation time of the first trial of St-D and St-T, was significantly greater than that of the average firing propagation time of the overall successful trial of St-D and St-T (P=0.03), while no significant difference was observed (P=0.77) between the first trial and the overall successful trial for St-L, as shown in Figure 8.

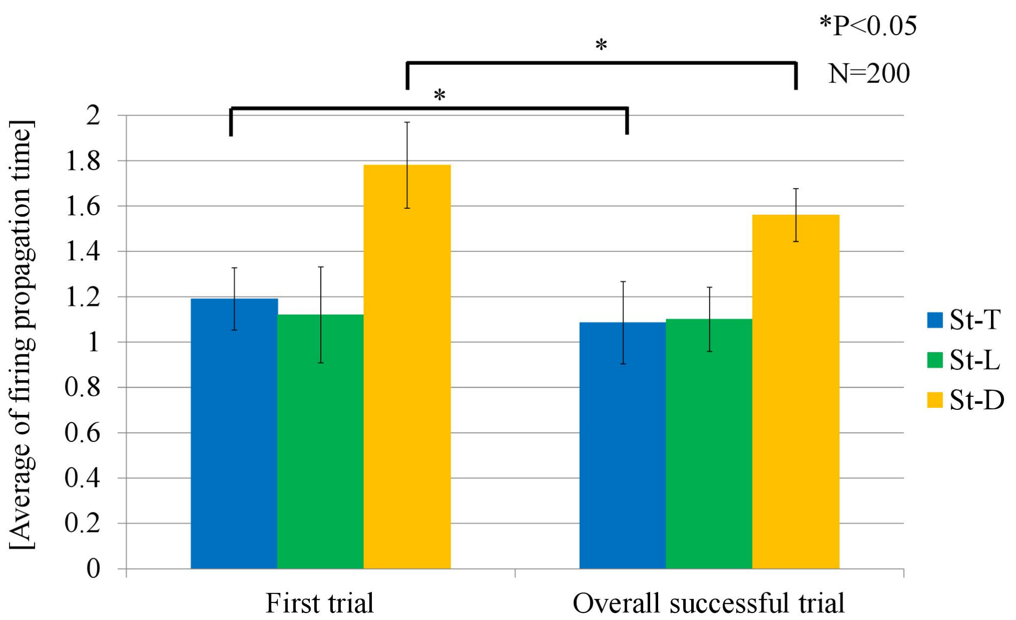

Figure 8. Decreasing firing propagation time by Hebb's reinforcement in three

channels. *P<0.05 between first trial and overall successful trial.

4. Discussion

In type M, all channels have a wide area where spike waves can propagate to multiplex transmission. Therefore, it was deduced that *learning time* is lower in type M channels. However, the two channels (green and yellow) of types H and V do not have a wide area where spike waves can propagate, as shown in Figure 9. Therefore, it was deduced that *learning time* is higher in these channels. The area where spike waves can propagate is restricted. Additionally, it is considered that *learning times* change depending on the arrangement of the stimulated neurons and the receiving neurons.

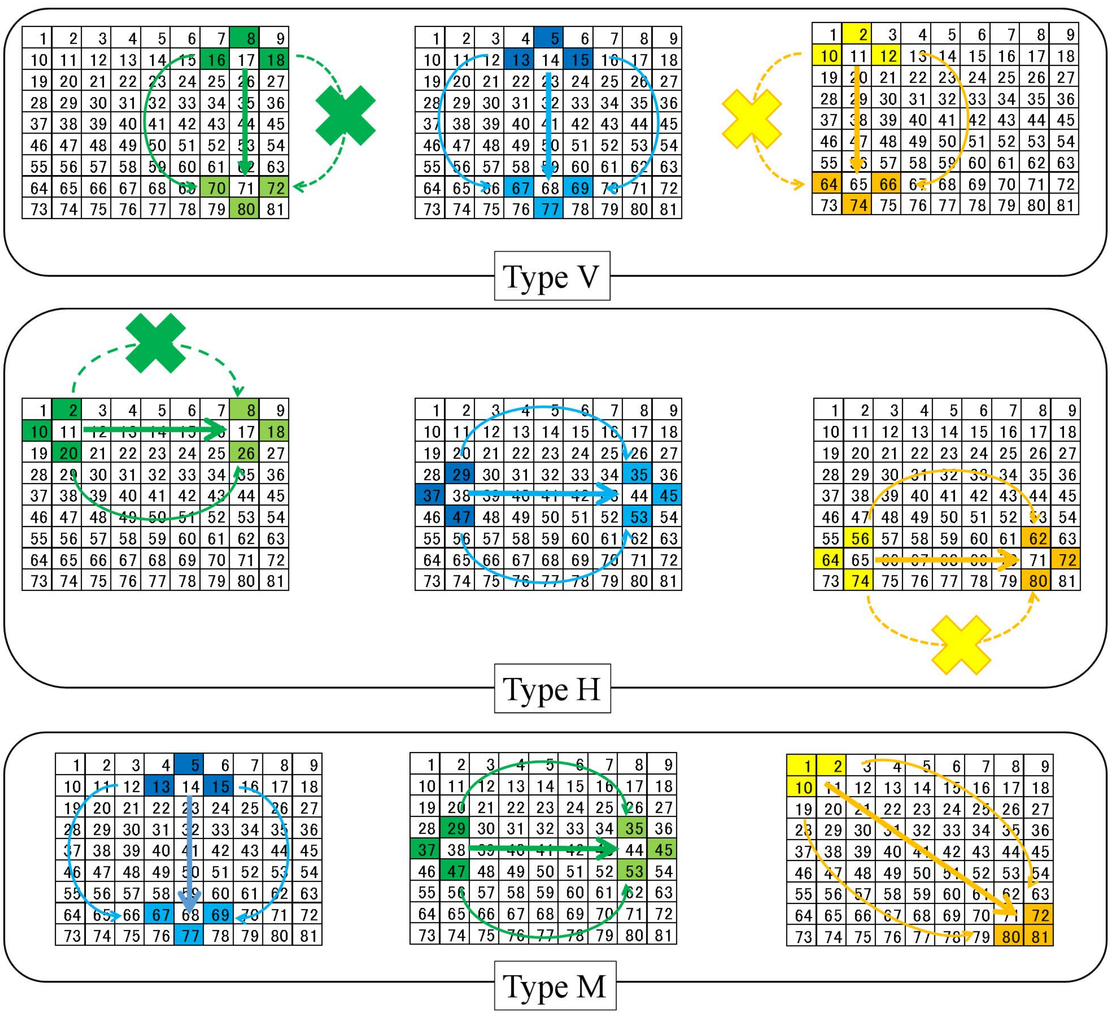

Figure 9. Area where spike waves can propagate.

Using type M, we calculated the firing propagation time in the first trial and the overall successful (in three channels) trial. Two of the three firing propagation times after the trial was successful were earlier than that of the first trial. The firing propagation times of St-T and St-L should be the same, because the position of transmission is only rotated by 90°. However, a difference between these two types may occur, as despite the firing propagation distances of St-T and St-L being the same, the learning process is performed in the order of St-T, St-L, and St-D. The learning process was performed until the receiving neuron could correctly identify the spike wave from the stimulated neuron group. Due to the existence of such an order, strengthening the weight of St-T could lead to the attenuation of the weight of St-L. Therefore, there is a possibility that a difference in the learning effect occurs.

In St-D, if the firing path (which is shown as the smaller activation time among neighboring neurons) is fixed, it was originally long, and there are many places where the weight could be strengthened. We speculate that the firing path was effectively shortened in the *overall success trial*. The weight between neurons is modified by the Hebb's rule. As a result, the firing path after learning is shorter than the firing path before learning, as shown in Figure 10. Shortening by Hebb's rule makes the propagation of the spike wave more circular. As a result, the event it induces the transmission time smaller, and the speed of the information transmission accelerates. Memory may be recall with memory reconstruction has been done with 2-8 times normal speed [29]. However, this paper does not include reconstruction of memory but shows only the effect of weight changes by Hebb's rule.

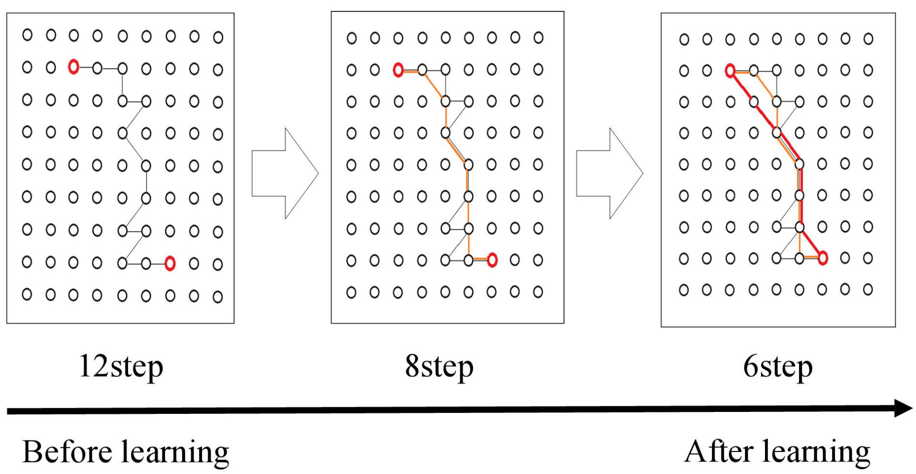

Figure 10. The firing path was effectively shortened by Hebb's rule. In the model, the

firing path was used only for illustration of the figure. Actually, there are variations in the instantaneous firing paths and there is no a certain path. The information is conveyed by a spike wave.

5. Conclusion

Novel ways of analyzing neuronal data are always being developed in the scientific community, in order to extract more information from the brain. Several studies focus on collecting data that provides with systems level information. Contrastingly, we have focused on elucidating the information regarding local, neuron-neuron connections, in order to understand the underpinnings of neuronal connectivity. In order to understand information processing in the brain, we conducted simulations of the firing activities of neural networks in the present study. We used an integrate-and-fire neuronal model without leakage and a 9 × 9 two-dimensional neural network. We showed how spikes were propagated from stimulated neurons to the receiving neurons in the simulation. During the simulation, spike propagation that occurred after the stimulated neuron group was first stimulated was observed for 10 ms. We set up three type simulations (types T, H, and M). In each type, a total of three stimulatory neurons (stimulated neuron groups) and receptive neurons (receiving neuron groups) were set. Using type M, we compared the firing propagation time in the first trial and the overall successful trial. The weight between neurons was modified by Hebb's rule. As a result, the firing path after learning is shorter than the firing path before learning. Therefore, we suggest that Hebb's rule contributes to the shortening of the firing path and contributes to speeding up communication in a neuron network. Though we could not post enough details here, we will present the details in another paper.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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