Increasing Selectivity to a Feature Combination Using Inhibitory Synaptic Plasticity in a Spiking Neural Network.

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Abstract

In this study, we designed a spiking neural network that uses synaptic plasticity to increase selectivity to a particular combination of features. We investigated how the time constant of inhibitory presynaptic neurons whose weights were updated by the long-term potentiation of inhibition affects to selectivity of the postsynaptic neurons. The results showed that the selectivity was increased effectively when the time constant of inhibitory neurons was slightly longer than that of postsynaptic neurons.

Keywords: spiking neural network, STDP, LTPi, combination of features

1. Introduction

In multi-layered neural networks for object classification, image features are extracted in each layer and are transferred to the latter layers. It is important for neurons in the intermediate layers to respond selectively to a combination of features because these combinations of features are essential for object classification. In the case of image classification, features are color, contour orientation, and so on.

A large majority of neural networks consist of so called artificial neurons whose inputs and outputs are represented by real numbers. However, actual neurons in the brain use pulsed potential changes called spikes for information transmission, not real numbers. Therefore, spiking neural networks, which mimic the cortical neuronal networks and consist of model neurons that use spikes for information transmission and processing, are expected to be the artificial intelligence of the next generation.

In the actual neuronal circuits, inhibitory neurons play an important role in information processing. Inhibitory neurons decrease the membrane potential of the postsynaptic neurons, and inhibition can increase the selectivity of the postsynaptic neurons to a particular set of stimuli by decreasing sensitivity to the other stimuli. A previous study suggested that long-term potentiation of inhibition (LTPi) is important in fine-tuning cortical circuitry in response to visual experience [1], and another study showed that LTPi can help spiking neural networks to respond to a specific stimulus-pair [2].

In this study, we designed a small network in which inhibitory neurons and their postsynaptic neurons respond to a combination of features and examined the relationship between the time constant of inhibitory neurons and selectivity of the postsynaptic neurons after training based on LTPi.

2. Models of Neurons and Synapses

2.1. *Model of neurons*

In this study, the leaky integrate-and-fire (LIF) model was used as a model of neurons [3]. The change in the membrane potential V_m of the LIF model is expressed as

$$RC\frac{dV_m(t)}{dt} = -(V_m(t) - V_r) + R\big(I_e(t) + I_i(t)\big). \quad (1)$$

The behavior at spike generation is given by

$$V_m(t) = V_R \quad \text{if} \quad V_m(t) > V_t. \quad (2)$$

Here, $I_e(t)$ and $I_i(t)$ represent excitatory postsynaptic currents (EPSCs) and inhibitory postsynaptic currents (IPSCs), respectively. C and R represent the membrane capacitance and resistance. V_r represents the resting membrane potential.

EPSCs increase the membrane potential, and the neuron generates a spike when the potential matches the condition expressed in Eq. (2). Generating a spike is called firing. After firing, the membrane potential decreases to the reset potential V_R , and the neuron enters the refractory period, during which the membrane potential does not change. In this study, we examined the relationship between time constant $\tau(= RC)$ and learning results.

EPSCs and IPSCs are calculated by the following equations:

$$I_e(t) = g_e\big(E_e - V_m(t)\big) \quad (3)$$
$$I_i(t) = g_i\big(E_i - V_m(t)\big) \quad (4)$$

g_e and g_i represent the excitatory and inhibitory synaptic conductance, respectively. E_e and E_i represent excitatory and inhibitory equilibrium potentials, respectively.

The model of input neurons is a Poisson process model. The number of spikes generated by the Poisson process model follows a Poisson distribution. The probability that spikes fire n times in interval Δt is given by

$$P[N(\Delta t) = n] = \frac{(\lambda\Delta t)^n}{n!}e^{-\lambda\Delta t}, \quad (5)$$

where λ represents the average rate at which spikes fire.

2.2. *Model of synapses*

We used a single exponential model for synapses. This model reproduces the exponential decay in the postsynaptic current after a spike firing of the presynaptic neuron. The exponential decay was applied to synaptic conductance g_e and g_i .

2.3. *Learning rule*

Many SNNs use the spike-timing dependent plasticity (STDP) [4], which models the biological synaptic plasticity, as a learning rule. The STDP changes the synaptic weights depending on the time difference between the firing of the presynaptic neuron and the postsynaptic neuron. The time difference causes a long-term potentiation (LTP) or a long-term depression (LTD) of the synaptic weights. This rule can train neurons that are selective to a particular set of stimuli.

In this study, synaptic weights of inhibitory inputs are strengthened by LTPi [2]. This learning rule strengthens inhibitory synaptic weights if the following two conditions are matched. First, the membrane potential of the postsynaptic neuron is higher than a certain value at the firing time of the presynaptic neuron. Second, the postsynaptic neuron does not fire during the time period just before and after the firing of the presynaptic (inhibitory) neuron. Under the conditions described above, inhibition is regarded as effective, and the inhibitory synaptic weight is strengthened. This behavior enables learning of a combination of features [2]. The weights of the inhibition (W) are updated by adding a constant value ΔW as the following equation:

$$W \leftarrow W + \Delta W. \quad (6)$$

3. Spiking Neural Network Configuration

Fig. 1 shows the neuronal network designed in this study. Each cluster with circles represents a group of neurons. The neural network consists of three layers: an input layer, an inhibition layer, and an output layer.

Input neuron groups A, B, and C are assumed to be groups of neurons that respond to three particular types of features. Each neuron in the output and inhibition layers is connected to two of the three groups of neurons in the input layer. Output neuron group α_o and inhibitory neuron group α_i are connected to groups B and C, β_o and β_i are connected to groups A and C, and γ_o and γ_i are connected to groups A and B. Each group in the inhibitory layer is connected to all the groups in the output layer. The output layer receives excitatory inputs from the input layer and inhibitory inputs from the

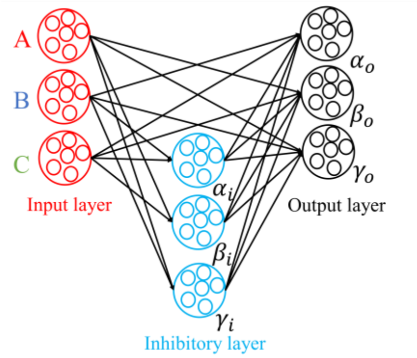

Fig. 1. Network structure. The number of neurons in the input, inhibitory, and output layers are 50, 10, and 30, respectively.

inhibitory layer. Only the weights between the inhibitory and output layers are updated by LTPi.

We set a probability of connection between two neuron groups. The probability between neurons in the input layer and the output layer is 50 %, that between the input layer and the inhibitory layer is 30 %, and that between the inhibitory layer and the output layer is also 30 %.

Because of the network topology, output neurons are selective to a set of input from the beginning. We examined whether the selectivity increases or decreases after learning.

4. Experiments and Results

4.1. *Training of the neural network*

To train the SNN, a pair of neuron groups in the input layer were activated for a certain period (100 ms). The firing rate was approximately 100 Hz. The pair of the groups was selected randomly, and the pair was changed every 100 ms. The membrane potential of each neuron was reset to its resting membrane potential when the pair was changed. The training period of 100 ms was repeated 100 times.

4.2. *Network output*

Fig. 2 shows a spike train of all neurons in the neuron group γ_o before and after training. The activated pair was changed every 50 ms in the test. The firing frequency was high during the period from 0 to 50 ms when the activated pair of the group was (A, B) because the pair is connected to γ_o. After training, the overall firing frequency decreased, but the decrease in the firing frequency during the period from 50 to 150 ms was more significant. Quantitative analysis is provided in the next section.

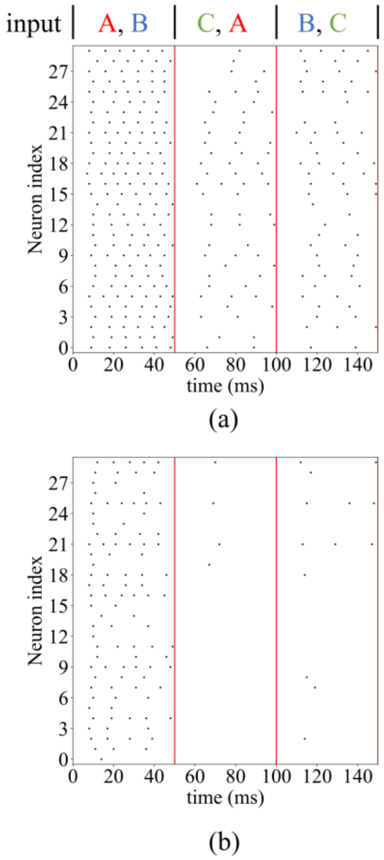

Fig. 2. Spike train of neurons in γ_o. (a) (b) show spikes before and after training, respectively. The time of firing is represented by a dot. The red line indicates the time of the change in the input pair, with an interval of 50 ms. The activated pair of neuron groups at each interval are shown in the upper part of the figure.

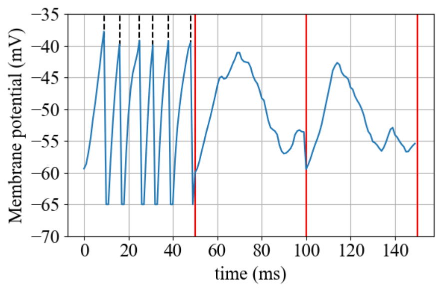

Fig. 3. Membrane potential of the output neuron whose index is nine in Fig. 2(b) after training.

Fig. 3 shows the membrane potential of neuron whose index is nine in Fig. 2(b). The vertical dashed line

Table 1 Average change in the synaptic weights before and after training. $\boldsymbol{W}_{\mathbf{pre}}$ and $\boldsymbol{W}_{\mathbf{post}}$ represent average weights before and after training, respectively.

Connection	$\boldsymbol{W}_{\mathbf{pre}}$	$\boldsymbol{W}_{\mathbf{post}}$	$\boldsymbol{W}_{\mathbf{post}} - \boldsymbol{W}_{\mathbf{pre}}$
$\boldsymbol{\alpha_i \to \gamma_o}$	0.073	0.449	0.376
$\boldsymbol{\beta_i \to \gamma_o}$	0.075	0.511	0.436
$\boldsymbol{\gamma_i \to \gamma_o}$	0.077	0.397	0.320

represents the time of firing. The membrane potential decreased significantly during the period from 50 to 150 ms because of the inhibitory input, resulting in preventing the neuron from firing. This result suggests that the selectivity increased.

Table 1 shows the average change of synaptic weights between neuron group γ_o and three neuron groups in the inhibitory layer before and after training. The change in weights between γ_i and γ_o was the smallest.

4.3. *Selectivity after training*

To evaluate the selectivity of neurons, we introduced a criterion that is given by the following equation:

$$S = \frac{1}{N}\sum_{n=1}^{N}\frac{F_i(n)}{F_{\mathrm{AB}}(n) + F_{\mathrm{BC}}(n) + F_{\mathrm{CA}}(n)}, \qquad (10)$$

where $F_i(n)$ ($i \in \{\mathrm{AB}, \mathrm{BC}, \mathrm{CA}\}$) represents the firing rate of an output neuron when the activated pair of neuron groups is i. N is the number of neurons in the neuron group. n represents the neuron index. The pair i of the numerator is the pair that the output neurons have the direct connection; for example, pair AB for neuron group γ_o.

We calculated the change in the selectivity criterion S for each neuron group. The amount of change is given by

$$\Delta S = S_{\mathrm{post}} - S_{\mathrm{pre}}, \qquad (11)$$

where S_{post} and S_{pre} represent the criterions after and before training, respectively.

Fig. 4 shows the relationship between the time constant of the inhibitory neurons and ΔS. Here, the time constant of the output neuron was set to 20 ms. We examined ΔS 10 times using different initial weights determined randomly. The value shown in Fig. 4 is the average of ΔS obtained in the 10 trials. The amount of increase in selectivity strongly depends on the time constant of the inhibitory neurons, and the time constant around 30 ms induced the largest increase in selectivity.

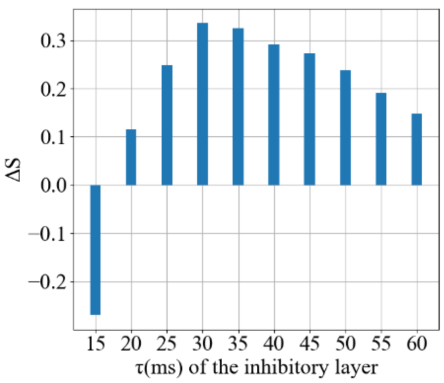

Fig. 4. Mean increase in selectivity of output neurons in γ_o

The increase in selectivity decreased gradually for time constants that is longer than 30ms. This indicates that appropriate parameter settings are necessary for increasing selectivity.

5. Conclusion

In this study, we designed a small spiking neural network that learns a combination of features by using LTPi. The selectivity examination showed that the amount of increase in selectivity strongly depends on the time constant of the inhibitory neurons.

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