Predictive Coding as Stimulus Avoidance in Spiking Neural Networks

Atsushi Masumori
Graduate School of Arts and Sciences
The University of Tokyo
Tokyo, Japan
masumori@sacral.c.u-tokyo.ac.jp

Takashi Ikegami
Graduate School of Arts and Sciences
The University of Tokyo
Tokyo, Japan
ikeg@sacral.c.u-tokyo.ac.jp

Lana Sinapayen
Sony Computer Science Laboratories, Inc.
Tokyo, Japan
Earth-Life Science Institute
Tokyo, Japan
lana.sinapayen@gmail.com

Abstract—Predictive coding can be regarded as a function which reduces the error between an input signal and a top-down prediction. If reducing the error is equivalent to reducing the influence of stimuli from the environment, predictive coding can be regarded as stimulation avoidance by prediction. Our previous studies showed that action and selection for stimulation avoidance emerge in spiking neural networks through spike-timing dependent plasticity (STDP). In this study, we demonstrate that spiking neural networks with random structure spontaneously learn to predict temporal sequences of stimuli based solely on STDP.

Keywords—Predictive coding; Spiking neural networks; Spike-timing dependent plasticity

I. INTRODUCTION

Prediction has recently been argued to be an important function of the brain [1], [2] and predictive coding [3], [4] has attracted the attentions of researchers in many fields [5], [6]. Predictive coding can be regarded as a function for reducing errors between an input signal and a top-down prediction. If reducing errors is equivalent to reducing the influence of environmental stimuli, predictive coding can be regarded as stimulation avoidance by prediction. Our previous studies showed that spiking neural networks with spike-timing dependent plasticity (STDP) [7] learn to avoid stimuli from the environment by their action [8], [9]. Cultured neural networks learn actions to avoid stimulation in the same way [10]. In addition, we found that neuronal cultures avoid stimulation by selecting what external information is received or declined [11]. In our previous study, we demonstrated that spiking neural networks with asymmetric STDP, in which the dynamics of long-term potentiation and long-term depression are rotational asymmetric, reproduced such selection. Therefore, based on STDP, two types of stimulation avoidance emerge: stimulation avoidance by action and stimulation avoidance by selection.

In this study, we evaluate whether prediction also emerges in spiking neural networks based on STDP. Several studies have examined the prediction of temporal stimulation in spiking neural networks [12], [13], [14]. However, these predictive networks require specifically designed network topology or other synaptic functions than STDP, such as short-term plasticity. We hypothesise that there is no need to include such structures or functions other than STDP for learning to predict a simple sequence of stimuli because our previous studies showed that neural networks with random initial weights learn to avoid stimuli by their action based on STDP, and for hidden neurons, a prediction that inhibits the input neurons response to stimulation is equivalent to an action that eliminates the stimulation.

We first demonstrate that minimal predictive networks consisting of 3 to 6 neurons with synaptic weight governed by STDP spontaneously learn to predict sequences of stimuli. We then show that even larger random networks (of 100 neurons) without a specifically designed structure spontaneously learn to predict sequences of stimuli based solely on STDP.

II. METHODS

A. Izhikevich Neuron Model

The spiking neuron model proposed by Izhikevich [15] was used to simulate excitatory and inhibitory neurons consisting small and large networks. This model is widely applied as individual parameters can be adjusted to reproduce the dynamics of many types of neurons, and it is also computationally efficient. The basic equations of this neural model are as follows:

\[
\begin{align*}
\frac{dv}{dt} &= 0.04v^2 + 5v + 140 - I, \\
\frac{du}{dt} &= a(bv - u), \\
\end{align*}
\]

if \( v \geq 30 \text{ mV} \), then \( \begin{cases} v \leftarrow c \\ u \leftarrow u + d. \end{cases} \) (1)

Here, \( v \) represents the membrane potential of the neuron, \( u \) is a variable related to membrane repolarization, \( I \) represents the input current (with multiple components as explained below), \( t \) is time, and \( a, b, c, \) and \( d \) are parameters controlling the shape of the spike [15]. The neuron is regarded as firing when the membrane potential \( v \geq 30 \text{ mV} \). The parameters for excitatory neurons were set to \( a = 0.02, b = 0.2, c = -65 \text{ mV}, \) and \( d = 8 \), and the parameters for inhibitory neurons to \( a = 0.1, b = 0.2, c = -65 \text{ mV}, \) and \( d = 2 \). With these parameters, excitatory neurons show regular spiking and inhibitory neurons show fast spiking (Fig. 1). The simulation time step \( \Delta t \) was set to 1 ms.

The variable \( I \) represents depolarization evoked by synaptic currents, noise, and external stimuli, and was added to the
membrane potential of each neuron $n_i$ at every time step as follows:

$$I_i = \sum_{j=0}^{n} f_j w_{ji} + e_i + m_i$$

(2)

$$f_j = \begin{cases} 1, & \text{if neuron } j \text{ is firing} \\ 0, & \text{otherwise.} \end{cases}$$

Here, $w_{ji}$ represents the weight of individual synapse between presynaptic neuron $j$ to postsynaptic neuron $i$, where weights are positive for synapse from excitatory neurons and negative for synapses from inhibitory neurons, $m$ is zero-mean Gaussian noise with standard deviation $\sigma = 3$ mV which represents the internal noise, $e$ represents the external stimulation (with conditions, frequency and strength of external stimulation varying among on experiments).

In most of the experiments, there was no synaptic delay; however, in the experiments with the longer temporal stimulus sequence (described below), a synaptic delay were added between an action potential of the presynaptic neuron and the postsynaptic potential. In these experiments, the function $f_j$ (Eq. 2) was modified by the synaptic delay according to

$$f_j = \begin{cases} 1, & t - ts_j = td_{ij} \\ 0, & \text{otherwise.} \end{cases}$$

where $t$ denotes the current simulation time, $ts_j$ represents spike timing of presynaptic neuron $j$, and $td_{ij}$ represents the synaptic delay between neuron $i$ and neuron $j$. In the experiments with synaptic delay, each pair of excitatory and inhibitory neuron was connected by 15 synapses and the $td$ of each synapse was varied from 1 to 15 ms.

### B. Spike-Timing Dependent Plasticity

Spike-timing dependent plasticity was used as the mechanism for changing synaptic weights between spiking neurons. In this model, synaptic weight increased when the presynaptic neuron fires before the postsynaptic neuron and decreased when the presynaptic neuron fires after the postsynaptic neuron. The weight variation $\Delta w$ is defined by

$$\Delta w = \begin{cases} A(1 - \frac{1}{\tau})^{\Delta t}, & \text{if } \Delta t > 0 \\ -A(1 - \frac{1}{\tau})^{-\Delta t}, & \text{if } \Delta t < 0. \end{cases}$$

(4)

Here, $\Delta t$ represents the relative spike timing between presynaptic neuron $a$ and postsynaptic neuron $b$; $\Delta t = t_b - t_a$ ($t_a$ represents the spike timing of neuron $a$, and $t_b$ represents the spike timing of neuron $b$). For excitatory synapses, $A = 0.1$ and $\tau = 20$ ms. Figure 2 shows the variation of $\Delta w$ depending on $\Delta t$; $\Delta w$ is negative when the postsynaptic neuron fires first and positive when the presynaptic neuron fires first. Note that STDP was applied not only to the connections between excitatory neurons but also to connections from inhibitory neurons to excitatory neurons. Although STDP at inhibitory synapse is still controversial, here we applied the reverse shape of the STDP function in Figure 2 for the inhibitory synapses ($A = -0.1$, $\tau = 20$).

The weight value $w$ varies as

$$w_t = w_{t-1} + \Delta w .$$

(5)

The maximum possible weight was fixed at $w_{max} = 80$ for excitatory synapses and $w_{max} = 0$ for inhibitory synapses, and if $w > w_{max}$, $w$ was reset to $w_{max}$. Alternatively, the minimum possible weight was fixed at $w_{min} = 0$ for excitatory synapses and $w_{min} = -80$ for inhibitory synapses, and if $w < w_{min}$, $w$ was reset to $w_{min}$.

### C. Experimental Setup

We first performed experiments with minimal predictive networks consisting of 3 to 6 neurons that learn to predict temporal sequences of stimuli. We then evaluated whether this learning performance is scalable to larger random networks of 100 neurons.

Figure 3 shows the basic network topology of the minimal predictive networks used in the first series of experiments, where $E_n$ represents excitatory neurons and $I$ represents an inhibitory neuron. The network consisted of excitatory input neurons and one inhibitory neuron. The input neurons were not connected to each other, but all were connected to and from the inhibitory neuron. The number of input neurons was varied.
from 3 to 5 across experiments. The initial weight values $w$ between neurons were set to 15 (in arbitrary units).

![Fig. 3. Basic topology of a minimal predictive network.](image)

The initial weight values $w$ between neurons were set to 15 (in arbitrary units).

We also constructed larger networks to evaluate the scalability of the predictive networks. These larger networks consisted of 80 excitatory neurons and 20 inhibitory neurons, and the network topology was random (i.e., neurons were fully connected with random weights). The weight values $w$ were randomly initialized between 0 and 5 ($0 < w < 5$) with uniform distributions for excitatory synapse and between -5 and 0 ($-5 < w < 0$) with uniform distributions for inhibitory synapse. Synaptic plasticity was applied to all connections except for connections between inhibitory neurons. There were three input neuron groups ($E_{G0}$–$E_{G2}$), each consisting of 10 excitatory neurons.

Three types of stimulus sequences were applied to the networks: a minimal pattern, a spatially extended pattern, and a temporally extended pattern (Fig. 4). The minimal pattern consisted of two stimuli, one signal stimulus followed by one target stimulus, where the signal stimulus was delivered to a specific input neuron and after a fixed time delay the target stimulus was delivered to another specific input neuron (Fig. 4A). Therefore, the timing of the signal stimulus was random (unpredictable) but the timing of the target stimulus was predictable. For the large networks, the minimal pattern consisted of two groups of synchronous stimuli with each stimulus group delivered to the corresponding input neuron group.

In the spatially extended pattern, the sequence consisted of four stimuli, one signal stimulus and three subsequent target stimuli. The signal stimulus was delivered to a specific input neuron and after a fixed time delay the target stimuli were delivered simultaneously to the three other specific input neurons (Fig. 4B).

In the temporally extended pattern, the sequence also consisted of four stimuli, one signal stimulus and three subsequent target stimuli. The signal stimulus was delivered to a specific input neuron and after a fixed time delay the first target stimulus was delivered to another specific input neuron followed by successive target stimuli at fixed time interval to other neurons (Fig. 4C).

For every sequence pattern, each stimulus produces a 100 mV depolarization in the minimal network and a 10 mV depolarization in the larger networks. The duration of each stimulus was set to 1 ms, the interval between each stimulus in the sequence to 10 ms (which is sufficiently smaller than the 20 ms working time window of STDP), and the interval between each sequence to 300 ms (which is sufficiently larger than the working time window of STDP). In addition to sequential stimulation, random stimulation was delivered into another specific input neuron (or input neuron group in large networks) as the control.

Prediction is defined here as suppression of the input neurons by the inhibitory neuron(s) at the time of stimulus input. This decrease the influence of environmental stimulation on the network; thus, prediction can be regarded as stimulus avoidance.
III. RESULTS

A. Minimal Networks

We first examined predictive coding by the smallest minimal network in response to the minimal stimulation pattern without synaptic time delay. The network consisted of three excitatory input neurons and one inhibitory neuron. The input neurons were not connected to each other, but all were connected bidirectionally to the inhibitory neuron (Fig. 3). If the target inputs are correctly predicted, spiking of input neurons should be inhibited at the timing of stimulation. We examined the firing rates of all input neurons and found that the firing rates of neuron $E_1$ receiving the target stimulus decreased, whereas the firing rates of neuron $E_0$ receiving the signal stimulus and $E_2$ receiving the random stimulus did not change substantially (Fig. 5). Therefore, the network gradually learned to predict the target stimuli (and exclude it) while the random stimulus was not predicted.

![Fig. 5. Time series of input neuron firing rates within small networks in response to the minimal pattern. The shaded regions represent the standard error of the mean ($n = 20$ networks). The firing rate of neuron $E_1$ receiving the target stimulus decreased substantially while the firing rates of neuron $E_0$ receiving the signal stimulus and $E_2$ receiving the random stimulus changed little.](image)

Figures 6 and 7 show that the weight of the synapse from the neuron receiving signal stimulation (the signal neuron $E_0$) to the inhibitory neuron increased with time, while the weight of the synapse from the inhibitory neuron to the target neuron ($E_1$) decreased with time. The path from $E_0$ to $I$ to $E_1$ is required to predict the timing of target stimuli at $E_1$. In contrast, the weights to and from the random neuron $E_2$ changed little.

We then evaluated whether small networks could learn to predict more complex spatially extended stimulus patterns (Fig. 4B) and temporally extended stimulus patterns (Fig. 4C). We first applied the spatially extended pattern of stimulation to networks with two more additional input neurons compared to the smallest minimal network shown in Fig. 3. Figure 8 shows that the firing rates of neurons $E_1$ to 3 receiving target stimuli in the spatial extended pattern decreased with time, whereas the firing rates of neuron $E_0$ receiving the signal stimulus and $E_2$ receiving the random stimulus did not change substantially. Therefore, the network gradually learned to predict the target stimuli (and exclude it) while the random stimulus was not predicted.

![Fig. 6. Time series of synaptic weight changes in small networks receiving the minimal stimulation pattern. The shaded regions represent the standard error of the mean ($n = 20$ networks). A: Weights from the inhibitory neuron to the excitatory neurons: $E_0$, $E_1$, and $E_2$. B: Weight from the excitatory neurons: $E_0$, $E_1$, and $E_2$ to the inhibitory neuron.](image)

![Fig. 7. Final topology of the smallest network after stimulation with the minimal pattern. The pathway from $E_0$ to the inhibitory neuron and from the inhibitory neuron to $E_1$ was strengthened. This pathway is required to predict target stimuli at $E_1$. The black arrows represent the excitatory synapses and the blue connections represent inhibitory synapses. The weight value of connections from the inhibitory neurons is negative.](image)
E4 receiving the random stimulus were largely unchanged. Thus, these small networks gradually learned to predict the spatially extended target stimulus pattern, while the random stimulus was not predicted. This implies that the inhibitory neuron suppressed the firing of neurons $E1-E3$ at the time of target stimulation and that the network learned to predict the spatially extended pattern.

On the other hand, these small network did not learn to predict the temporal extended pattern. Figure 9A shows that the only firing rate of neuron $E1$ decreased with time. This implies that the network cannot learn to predict the longer temporal sequence than the minimal pattern consists of two stimuli, possibly, because there is only one inhibitory neuron and one connection to each excitatory neuron and longer temporal information cannot be encoded.

For neural networks to predict a longer temporal sequence, we hypothesized that they must have more inhibitory neurons or more synapses between the input neurons and inhibitory neurons with different synaptic delays to encode temporal information. Therefore, we constructed a small model with 15 synapses between each input neuron and the inhibitory neuron and set different time delays (from 1 to 15 ms).

Figure 9B shows that the firing rates of neurons $E1-E3$ receiving target stimuli in the temporal sequence decreased whereas the firing rates of $E0$ receiving the signal stimulus and $E4$ receiving the random stimulus changed little. Thus, these networks gradually learned to predict the temporal sequence, while the random stimulus was not predicted. This implies that the inhibitory neuron suppressed spiking of neurons $E1-3$ at the time of target input and that small networks with synaptic delay can learn to predict temporal sequences.

**B. Large Random Networks**

We then examined whether the learning properties of these minimal networks are scalable to large networks. We applied the minimal pattern of stimulation to random networks with 100 neurons. Figure 10 shows that these larger networks gradually learned to predict the minimal pattern, while the random stimulation was not predicted. The green line represents the firing rate of hidden neurons, which can be regarded as the baseline firing rate of the network. The firing rate of excitatory neuron group 1 (EG1) receiving target stimuli gradually decreased to near baseline levels, indicating reasonable prediction accuracy.

Figure 11 shows a typical example of raster plot of spikes for each neuron in the large network. In the first phase of the experiment (first 3000 ms), almost all neurons of group EG1 fired immediately in response to the target stimuli while in the later phase (final 3000 ms), the firing rate was much lower and the pattern was very similar to that of the hidden neurons. This
implies that inhibitory neurons suppressed the firing of $EG_1$ neurons at the time of target stimulation, suggesting that large random networks can learn to predict the minimal pattern of stimulation using only STDP.

Moreover, the time series of synaptic weight changes between neuron groups resembles those of the small networks (Fig. 12), suggesting that the mechanisms underlying prediction are similar.

Figure 13 shows the final topology of the network. There was a strong pathway from $EG_0$ to inhibitory neurons and from inhibitory neurons to $EG_1$; This pathway is required for the prediction. In addition, there was a pathway from $EG_0$ to the hidden neurons, from the hidden neurons to the inhibitory neurons, and from the inhibitory neurons to $EG_1$. This pathway may be required to adjust the timing of $EG_1$ suppression.

Collectively, these findings demonstrate that the learning performance of small minimal networks is scalable to larger random networks. Thus, spiking neural networks without specific structure (random networks) can spontaneously learn to predict simple stimulus sequences based solely on STDP.

IV. DISCUSSION

We demonstrate that spiking neural networks can spontaneously learn to predict input sequences from the environment based only on STDP. The firing of input neurons receiving target stimuli (those following signaling inputs) were predicted and suppressed by inhibitory neurons, thereby reducing the influence of environmental stimulation on network activity. In other words, neural networks can learn to avoid (ignore) specific input stimulation pattern through STDP.

We also demonstrate that this property is scalable from small networks of a few neurons to larger random networks of 100 neurons without specific design structures or other functions except STDP. These findings also suggest that like stimulation avoidance by action and selection in neuronal cultures [16], [11], prediction can emerge to avoid stimulation...
in neuronal cultures via STDP, although this notion remains to be confirmed.

Our previous studies showed that action and selection can emerge in spiking neural networks based on STDP and that these mechanisms can eliminate specific stimulus inputs [17]. In this study, we found that stimulation avoidance by prediction also emerges in spiking neural networks based on STDP and that these mechanisms can eliminate specific stimulus inputs [17].

In this study, we found that stimulation avoidance by prediction also emerges in spiking neural networks based on STDP and that these mechanisms can eliminate specific stimulus inputs [17].

in Grant-in-Aid for Scientific Research on Innovative Areas “Correspondence and Fusion of Artificial Intelligence and Brain Science” (19H04979)

REFERENCES

[1] A. M. Bastos, W. M. Usrey, R. A. Adams, G. R. Mangun, P. Fries, and K. J. Friston, “Canonical Microcircuits for Predictive Coding,” pp. 695–711, 2012.
[2] A. Clark, “Whatever next? predictive brains, situated agents, and the future of cognitive science,” Behavioral and Brain Sciences, vol. 36, no. 3, pp. 181–204, 2013.
[3] R. P. N. Rao and D. H. Ballard, “Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects,” Nature Neuroscience, vol. 2, no. 1, pp. 79–87, 1999.
[4] Y. Huang and R. P. N. Rao, “Predictive coding,” Wiley Interdisciplinary Reviews: Cognitive Science, vol. 2, no. 5, pp. 580–593, 2011.
[5] K. Friston and S. Kiebel, “Predictive coding under the free-energy principle,” Philosophical Transactions of the Royal Society B: Biological Sciences, vol. 364, no. 1521, pp. 1211–1221, 2009.
[6] W. Lotter, G. Kreiman, and D. Cox, “Deep predictive coding networks for video prediction and unsupervised learning,” in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings, 2017.
[7] S. Song, K. D. Miller, and L. F. Abbott, “Competitive Hebbian learning through spike-timing-dependent synaptic plasticity,” Nature neuroscience, vol. 3, no. 9, pp. 919–26, sep 2000.
[8] L. Sinapayen, A. Masumori, and T. Ikegami, “Learning by stimulation avoidance: A principle to control spiking neural networks dynamics,” PLOS ONE, vol. 12, no. 2, p. e0170388, feb 2017.
[9] A. Masumori, L. Sinapayen, and T. Ikegami, “Learning by stimulation avoidance scales to large neural networks,” in Proceedings of the 14th European Conference on Artificial Life ECAL 2017. Cambridge, MA: MIT Press, sep 2017, pp. 275–282.
[10] A. Masumori, N. Maruyama, L. Sinapayen, T. Mita, U. Frey, D. Bakkum, H. Takahashi, and T. Ikegami, “Learning by Stimulation Avoidance in Cultured Neuronal Cells,” in The 2nd International Symposium on Swarm Behavior and Bio-Inspired Robotics (SWARM2017), 2017.
[11] A. Masumori, L. Sinapayen, N. Maruyama, T. Mita, D. Bakkum, U. Frey, H. Takahashi, and T. Ikegami, “Autonomous regulation of self and non-self by stimulation avoidance in embodied neural networks,” The 2018 Conference on Artificial Life: A Hybrid of the European Conference on Artificial Life (ECAL) and the International Conference on the Synthesis and Simulation of Living Systems (ALIFE), pp. 163–170, 2018.
[12] D. V. Buonomano, “Decoding temporal information: A model based on short-term synaptic plasticity,” Journal of Neuroscience, vol. 20, no. 3, pp. 1129–1141, 2000.
[13] R. P. N. Rao and T. J. Sejnowski, “Spike-timing-dependent hebbian plasticity as temporal difference learning,” Neural Comput., vol. 13, no. 10, pp. 2221–2237, Oct. 2001.
[14] C. Wacongne, J.-P. Changeux, and S. Dehaene, “A Neuronal Model of Predictive Coding Accounting for the Mismatch Negativity,” Journal of Neuroscience, vol. 32, no. 11, pp. 3665–3678, 2012.
[15] E. Izhikevich, “Simple model of spiking neurons,” IEEE Transactions on Neural Networks, vol. 14, no. 6, pp. 1569–1572, 2003.
[16] A. Masumori, N. Maruyama, L. Sinapayen, T. Mita, U. Frey, D. Bakkum, H. Takahashi, and T. Ikegami, “Emergence of Sense-Making Behavior by the Stimulus Avoidance Principle: Experiments on a Robot Behavior Controlled by Cultured Neuronal Cells,” Proc. of the European Conference on Artificial Life (ECAL) 2015, pp. 373–380, 2015.
[17] A. Masumori, L. Sinapayen, N. Maruyama, T. Mita, D. Bakkum, U. Frey, H. Takahashi, and T. Ikegami, “Neural Autopoiesis: Organizing Self-Boundary by Stimulus Avoidance in Biological and Artificial Neural Networks,” Artificial Life, vol. in press, 2019.

ACKNOWLEDGMENT

This work is partially supported by MEXT project “Studying a Brain Model based on Self-Simulation and Homeostasis”