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A Simulation Study of Visual Perceptual Learning with Attentional Signals

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Abstract: Repeated exposure to a specific stimulus can enhance animal's sensitivity to it so that the perceptual capability is improved. This experience-induced perceptual improvement is referred to as perceptual learning. However, the neural system has some robustness and is not necessarily modified by its any input. In the case of visual perceptual learning (VPL), perceptual performance for a task-relevant stimulus can be selectively improved without any sensitivity change to task-irrelevant stimuli which are presented even simultaneously with the task-relevant one. In this study, we propose a feed-forward spiking neural network model consisting of a primary visual cortex (V1) layer and a higher visual area (V4) layer; their inter-layer feed-forward connections are modified by synaptic learning in a particular interest in how VPL can be affected by neural activities in the higher area due to attentional signals. Through simulations, we show attentional inputs are needed to facilitate inter-layer synaptic learning which yields improved sensitivity to the task-relevant stimulus, and thus to increase the task performance.

Keywords: Perceptual learning, Visual attention, Spiking neural network, Spike-timing dependent plasticity

I. INTRODUCTION

Animal's brain continues to modify the structures of its neural networks to adapt to environmental changes even after its maturation. Repeated exposure to a specific stimulus can enhance animal's sensitivity to it so that the perceptual capability is consequently improved. This experience-induced perceptual improvement is referred to as perceptual learning. However, the neural system has some robustness and is not necessarily modified by its any input. In the case of visual perceptual learning (VPL), perceptual performance for a task-relevant stimulus can be selectively improved without any sensitivity change to task-irrelevant stimuli which are presented even simultaneously with the task-relevant one. These observations raise the following questions: what is the computational basis of VPL and how does the brain accomplish VPL in such a noisy environment with appropriately detecting relevant information?

There is a hypothesis that VPL is due to changes in synaptic connections between neurons of the primary visual cortex which acts as feature extractors of visual elements and those of the higher visual cortical areas which are involved in decision making functions [1]. A preceding study reported that the bell-shaped tuning curve for the task-relevant stimulus gets sharpened in V4 neurons which receive inputs from V1 neuronal population, but not in V1 neurons [2], supporting this hypothesis. In terms of Fisher information, sharpening of a tuning curve leads to increase in information, suggesting the improvement of representation of sensory information encoded by neuronal population [3]. In addition, it has been suggested that active and persistent attention to a feature to be learned is also needed for VPL [4]; one of the previous studies reported that when two different stimuli were presented simultaneously but the subject was required to pay attention to one of them, no VPL occurred for the stimulus to which the subject did not pay attention [5]. Another existing study reported that responses of V4 neurons to a particular stimulus with paying attention were significantly higher than those without paying attention [6], which also suggested the existence of attentional control on VPL.

Nevertheless, there is still a missing link; no previous study has clarified the direct relationship between sharpening of tuning curves of V4 neurons and connection changes between V1 and V2 which is affected by the attentional control during VPL. For unified explanation of attentional effects on V4 neurons and sharpening of their tuning curves induced by VPL, we propose in this study a feed-forward spiking neural network model which includes a V1 layer and a V4 layer; neurons in the V4 layer receive inputs from neurons in the V1 layer and also top-down attentional excitatory signals. Performing a learning simulation of this network, we show that the task performance is improved due to changes in neuronal connections, and is more facilitated by V4's activities enhanced by the attentional signals.

II. MODEL

In this study, we used a grating task [7] for simulating a VPL situation. In a single trial of the real grating task, two grating images are sequentially presented to a subject; the second grating image is rotated from the first one. Then a subject is required to answer whether the tilt orientation of the second image has changed from that of the first one in a clockwise manner or in a counterclockwise manner. A previous experimental study observed that repeated exposure to such grating stimuli induces changes in tuning curves of V4 neurons [2]. According to the hypothesis that VPL is due to connectional changes between neurons of the primary visual cortex and those of the higher visual cortical areas [1], it is thought that changes in V4 responses are mainly due to connectional changes between V4 and V1 neurons; the former corresponds to the higher visual cortical area and is projected by the foveal region of V1 directly [8], and the latter codes tilt orientation of presented grating stimuli by means of its orientation selectivity. Based on these assumptions, in this study, we propose a hierarchical and feed-forward neural network model which consists of two neuronal layers of V1 and V4 where connections between the layers can be modified by a spike-timing dependent plasticity (STDP) rule (Fig. 1). In the actual experimental setting, a subject would be exposed not only to the target stimuli but also to many distracters; however, in this study we assume that the model neurons respond only to grating image stimuli for simplicity. We present the details of the model in the following sections.

1. V1 layer

The V1 layer consists of 80 model neurons each of which was implemented as a Poisson spike generator with frequency $r(\theta_{\text{input}})$; the frequency was given by a Gaussian-like neuronal response function with a preferred orientation θ_{PD}, to the tilt orientation of an input grating stimulus θ_{input}:

$$\begin{aligned} r(\theta_{\text{input}}) &= a\exp\left(\frac{-\left|\theta_{\text{input}}-\theta_{\text{PD}}\right|}{2\sigma_{\text{r}}^2}\right)+R, \\ \theta_{\text{PD}} &= \bar{\theta}_{\text{PD}}+\Delta\theta_{\text{PD}}, \\ \bar{\theta}_{\text{PD}} &\in \{n\pi/8\}\ (n=0,\ldots,7), \quad \Delta\theta_{\text{PD}} \sim N(0,\sigma_{\text{PD}}^2), \end{aligned} \tag{1}$$

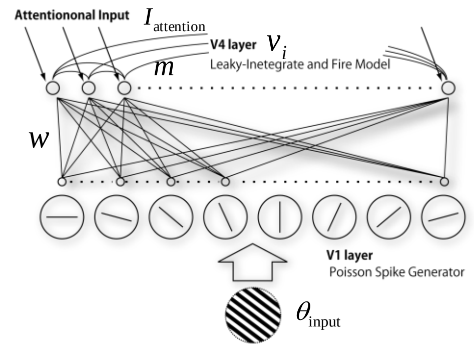

Fig.1. The architecture of network model

where a, σ_{r} and R are constants; we set $a=0.02$, $\sigma_{\text{r}}=0.5$ and $R=0.002$ in the simulation. Each V1 neuron has own orientation selectivity to gratings (σ_{r}) and the preferred tilt orientation (θ_{PD}). The V1 layer consists of 8 groups of 10 neurons which have different orientation preference (Fig. 1); the preferred orientations of the 10 neurons in each group do not vary so much around its average $\bar{\theta}_{\text{PD}}$, but they have different means between the 8 groups.

2. V4 layer

The V4 layer consists of 100 neurons each of which was implemented as a leaky-integrate and fire neuron model:

$$\begin{aligned} \tau_{\text{v}}\frac{dv_i}{dt} &= -(v-V_{\text{rest}})+I_i+I_{\text{attention}}, \\ v_i &\leftarrow V_{\text{rest}} \text{ if } v_i \geq V_{\text{threshold}}, \end{aligned} \tag{2}$$

where τ_{v} is a membrane time constant. v_i, V_{rest}, and $V_{\text{threshold}}$ are membrane potential, resting potential, and firing threshold, respectively. In this study, we set $\tau_{\text{v}}=1$, $V_{\text{rest}}=-64$ and $V_{\text{threshold}}=30$. I_i and $I_{\text{attention}}$ represent input current and attentional input current, respectively. A V4 neuron i receives synaptic currents I_i from V1 and V4 neurons:

$$\begin{aligned} I_i &= \int_0^t f(t-t')\left\{\sum_j w_{ij}u_j^{\text{v1}}(t')+\sum_k m_{ik}\,u_k^{\text{v4}}(t')\right\}dt', \\ f(t) &= \frac{t}{\tau_{\text{u}}}e^{1-t/\tau_{\text{u}}}, \end{aligned} \tag{3}$$

where $u_j^{\text{v1}}(t)$ and $u_j^{\text{v4}}(t)$ represent indicator functions of spike occurrences at V1 neuron j and V4 neuron i, respectively. When a spike occurs in V1 (V4) neuron $j(i)$ at t, $u_{j(i)}^{\text{v1(v4)}}(t)=1$ and otherwise $u_{j(i)}^{\text{v1(v4)}}(t)=0$. w_{ij} is synaptic strength of feed-forward connection from V1 neuron j to V4 neuron i, and m_{ik} is synaptic strength of recurrent connection from V4 neuron k to V4 neuron i. In this study, we set $m_{ik}=0.1(i=k)$ or $-0.04(i\neq k)$. $f(t)$ is a spike response function with the time constant of $\tau_{\text{u}}(=1.5)$.

3. Spike-timing dependent plasticity

During VPL, synaptic strength w_{ij} between a V1 neuron *j* and a V4 neuron *i* was updated by an additive STDP rule [9] as follows:

$$w_{ij} \leftarrow w_{ij} + \Delta w,$$
$$\Delta w = \begin{cases} \alpha_+ \exp\left(-\frac{|\Delta t|}{\tau_+}\right) & \text{if } \Delta t \geq 0, \\ -\alpha_- \exp\left(-\frac{|\Delta t|}{\tau_-}\right) & \text{if } \Delta t < 0, \end{cases}$$
$$\Delta t = t_i - t_j, \tag{4}$$

where t_i and t_j are spike timing of neuron *i* (post) and *j* (pre), respectively. $\alpha_+ (\alpha_-) > 0$ and τ_+ (τ_-) define the maximum amount of synaptic change and the time constant of long-term potentiation (depression). We used $\alpha_+ = 0.0103$, $\alpha_- = 0.0051$, $\tau_+ = 13.3$ and $\tau_- = 34.5$ in this study. On the other hand, we assumed that the connections within the V4 layer did not change, so they were fixed during VPL.

III. SIMULATION EXPERIMENTS

1. Simulation procedures

To examine the effects of top-down attentional inputs on VPL, we conducted a network simulation assuming the grating task. First, we initialized the synaptic connections between V1 and V4 neurons w_{ij} by presenting 20,000 uniformly random stimuli θ_{input} to the model network. This initial phase encouraged each V4 neuron to form a sparse receptive field for input stimuli, which is similar to the result by the sparse coding scheme [10]. An example of the resultant tuning curves which correspond to responses of V4 neurons to orientation of input grating stimuli are presented in Fig.2.

We then trained our model network by simulating the grating task. In a single simulation trial of the grating task, two grating stimuli were successively presented to the model network for 300 ms each. Tilt of the first grating was fixed to the base orientation $\theta_{\text{input}} = \theta_{\text{o}}$, and that of the second one was $\theta_{\text{input}} = \theta_{\text{o}} + \theta_{\text{d}}$ in each trial. In this simulation, we set $\theta_{\text{o}} = 24°$ and θ_{d} was randomly drawn from a uniform distribution of *U*(-10, 10).

2. Evaluation of attentional effects

To evaluate how the VPL proceeds in the model network, we calculated normalized tuning curves of V4 neurons, each of which was the connection-weighted summation of tuning curves of V1 neurons and normalized to make its maximum response a fixed value.

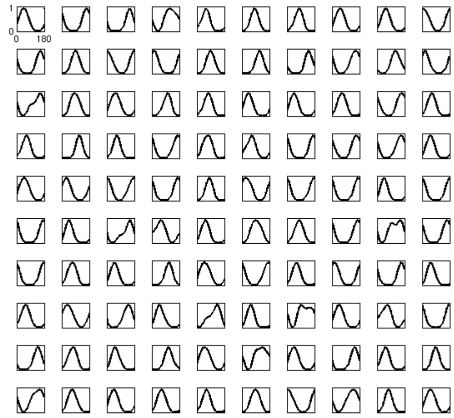

Fig.2. Orientation selectivity of V4 neurons before VPL. Each tuning curve was calculated based on tuning curves of V1 cells weighted by the connection values from the V1 cells to the corresponding V4 cell. The horizontal axis represents tilt of input grating stimuli and the vertical axis represents the normalized response. It is assumed that the V4 network can decode the orientation of input grating by integrating the patterns of V4 responses.

We then estimated "sharpness" of each V4 neuron to measure the degree of sensitivity to input stimuli by fitting its normalized tuning curve to a Gaussian function and then obtaining its variance. Finally, we tested how the sharpness of the neuronal population changed between before and after the VPL phase based on one-sided t-test [2]. Since we are also interested in the dependence of VPL on the top-down attentional signals, we conducted the simulation above by changing the level of attentional inputs.

IV. RESULTS

After simulating the model network in the grating task by setting various levels of attentional siginals, $I_{\text{attention}} = \{0,...,30\}$, we obtained tuning curves after learning (Fig. 3). This figure shows that the turning curves of some V4 neurons got sharpened significantly after VPL with a relatively large level of attentional signals ($I_{\text{attention}} = 22$), which is consistent with the existing experimental result in which tuning curves of V4 neurons became sharpened after VPL [2]. Fig. 4 shows histograms of sharpness of tuning curves of V4 neurons, before learning (upper panel) and after learning with no attentional inputs (middle panel) and relatively large attentional inputs (lower panel). The sharpening of tuning curves after VPL occurred in the population-wide manner in the V4 layer regardless of the level of attentional inputs, whereas the stronger attentional signals likely induced sharper tuning curves ($I_{\text{attention}} = 0, p = 0.065$ and $I_{\text{attention}} = 22, p = 0.0011$). In addition, the minimum value of the sharpness with $I_{\text{attention}} = 22$ ($18.8°$) was smaller than that with $I_{\text{attention}} = 0$ ($23.1°$). On the other hand, too large attentional inputs induced broader tuning curves; indeed, mean sharpness after VPL with $I_{\text{attention}} = 30$ was $39.9° \pm 0.00°$ (the initial mean sharpness was $30.0° \pm 8.7°$). These results imply that appropriate level of attentional control to V4 neurons would work for promoting perceptional sensitivity.

V. DISCUSSION AND CONCLUSION

In this study, we simulated network learning in which synaptic connections between V1 and V4 neurons were modified by STDP during the grating task, and showed that our network model well reproduced sharpening of tuning curves of the V4 neurons. We also found that moderate attentional inputs yield sharpen tuning curves of the V4 neurons. These results impy that appropriate level of attention contributes to facilitating VPL while VPL occurs even without paying attention. In our network model, reductions in connectional strength between V1 and V4 neurons were often observed in V4 neurons which acquired sharpened tuning curves (result not shown). These synaptic reductions can depress responses of V4 neurons to input stimuli, while a previous study reported increase in spike frequency after VPL [2]. This inconsistency may be resolved by introducing backward attentional control from V4 to V1, as suggested in a previous study [11]. Backward attentional pathway would increase spike frequency of V1 neurons such to facilitate activities of the projected V4 neurons. In future work, therefore, we will examine attentional effects in VPL by cortical model networks including mutually-connected V1 and V4 layers.

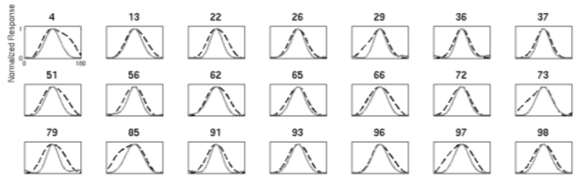

Fig.3. Tuning curves of V4 neurons before (dashed line) and after (solid line) 5,000 gating task trials with attentional input of $I_{\text{attention}} = 22$. Each tuning curve was rescaled and shifted to adjust the peak to the center of the horizontal axis.

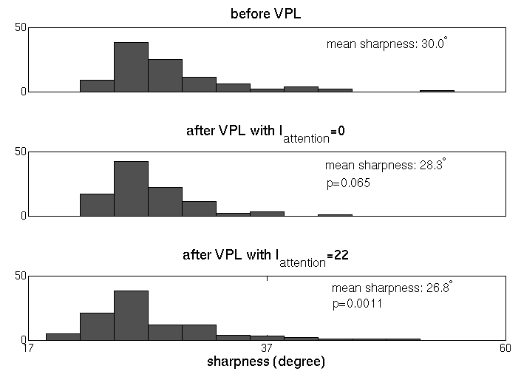

Fig.4. Histogram of sharpness of tuning curves of V4 neurons. Upper: before learning. Middle: after learning with no attentional inputs ($I_{\text{attention}}$ = 0). Lower: after learning with a relatively strong attentional inputs ($I_{\text{attention}}$ = 22).

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