

Analysis of Neural Circuit for Visual Attention Using Lognormally Distributed Input

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Abstract. Visual attention has recently been reported to modulate neural activity of narrow spiking and broad spiking neurons in V4, with increased firing rate and less inter-trial variations. We simulated these physiological phenomena using a neural network model based on spontaneous activity, assuming that the visual attention modulation could be achieved by a change in variance of input firing rate distributed with a lognormal distribution. Consistent with the physiological studies, an increase in firing rate and a decrease in inter-trial variance was simultaneously obtained in the simulation by increasing variance of input firing rate distribution. These results indicate that visual attention forms strong sparse and weak dense input or a ‘winner-take-all’ state, to improve the signal-to-noise ratio of the target information.

Keywords: Visual Attention, Neural Network Model, Spontaneous Activity, Lognormal Distribution.

1 Introduction

Recent physiological studies have revealed that visual attention modulates neural activity depending on the cell types in V4 [1–4]. Specifically, narrow spiking (NS) neurons and broad spiking (BS) neurons, which are classified according to the spiking waveforms, have been both reported to exhibit increased firing rate and decreased Fano factor for attention [5]. Fano factor is the ratio of spike count variance to mean spike count and decreases when a certain part of cortex receives input [6], especially during attention [5, 7, 8]. NS and BS neurons have been reported to correspond to inhibitory interneurons and excitatory pyramidal neurons, respectively [9–11]. They reported that the increase in the firing rate of NS neurons have been globally observed much larger than that of BS neurons during a visual attention task, and some BS neurons exhibit decreased firing rate by analyzing individual neuronal behaviors. Because both increased and decreased types of BS neurons exist to a similar extent, no clear attention modulation can be totally seen in appearance.

Despite such physiological phenomena, the mechanism of how these phenomena are achieved in the neural circuit have not been formulated. In this study,

we simulated the NS and BS neural activity for visual attention using the strong sparse and weak dense (SSWD) model by Teramae et al. [12]. We assumed that the visual attention modulation could be achieved by the change in variance of input firing rate distributed with a lognormal distribution. Under this assumption, the simulated neural activity for the input was evaluated by the firing rate and Fano factor. Moreover, we evaluated neural activity by attention index that were used in Mitchell et al. [5]. The attention index enables us to analyze the effect of visual attention modulation to individual neurons. Using these indices, we tested the relationship between lognormally distributed input and its output during visual attention at the neural circuit level.

2 Neural Activity Simulation

2.1 Original Physiological Experiment

We simulated neural activity during a visual attention task, according to a physiological study achieved by Mitchell et al. [5]. This task was comprised of five periods: CUE, SHUFFLE, PAUSE, SHUFFLE, and SACCADE. Four identical Gabor patterns were presented to the macaque monkeys. In CUE, two patterns were flashed so that the monkeys could mentally track the patterns. The locations of these targets and the other two distracters were randomly shuffled in the first SHUFFLE. Then, all the stimuli stopped for 1 s (PAUSE), with one of the stimuli placed within the visual receptive field (RF). The locations were shuffled again in the second SHUFFLE. Finally, behavioral performance was evaluated in SACCADE by checking if they moved their eyes toward appropriate stimuli.

The neural activities in PAUSE were mainly analyzed. They regarded the condition where the target stimulus was placed within the RF as the attended condition, and the other as the unattended condition. Fig.1 A and C show the averaged activities of the 109 visually responsive BS neurons for the attended (dark blue) and unattended (light blue) stimuli, and Fig.1 B and D show those of the 43 NS neurons for the attended (dark red) and unattended (light red) stimuli. BS and NS neurons showed increased firing rate when a stimulus was placed within the RF. In addition, the firing rates became much larger when the stimulus within the RF was a target as compared with a distracter. Besides, the Fano factor was fluctuated in inverse proportion to the firing rate.

Fig.1 E and F show the individual neural activity by attention index (AI). AI is expressed as $(A - U)/(A + U)$, where A is an attended value and U is an unattended value calculated by averaging either firing rate or Fano factor over 1-s PAUSE. The individual Fano factors for NS and BS neurons were low in the attended condition. Although most of NS and BS neurons showed high firing rates, some BS neurons were significantly low in the attended condition. They thus claimed that NS neurons are much more important for visual attention.

2.2 Neural Network Model

Irregular spontaneous neuronal firing of cerebral cortex (< 10 Hz, typically 1–2 Hz) reflects various cognitive functions [13]. Because spontaneous firing in V4

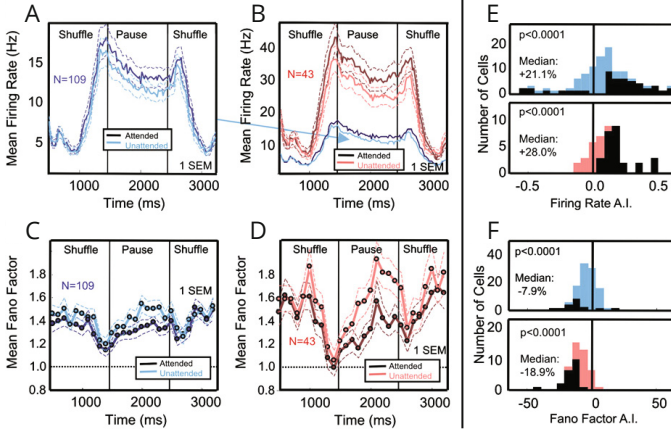


Fig. 1. Comparison of attention-dependent modulation of rate and Fano factor in BS and NS neurons, adapted from Mitchell et al. [5]. A and B: average firing rate of BS (blue) and NS (red) neurons for attended (dark color) and unattended (light color) conditions. C and D: average Fano factor for attended and unattended conditions. E: distribution of attention index for a firing rate. F: attention index for a Fano factor. Significant modulation are indicated in black.

was reported to fluctuate with visual attention [1] and evaluation of neuronal variability is crucial for this study, we used the SSWD recurrent network model proposed by Teramae et al. [12]. The model is obtained by modifying the leaky integrate and fire neuron model using synapse transmission delay d_j . Only the first trigger input exhibits asynchronous spontaneous spiking activity. Dynamics of the membrane potential v and synapse conductance g can be expressed as Eqs. 1 and 2.

$$\frac{dv}{dt} = -\frac{1}{\tau_{mX}}(v - V_L) - g_E(v - V_E) - g_I(v - V_I) \quad (1)$$

$$\frac{dg_X}{dt} = -\frac{g_X}{\tau_S} + \sum_j G_{X,j} \sum_{s_j} \delta(t - s_j - d_j), \quad (X = E, I) \quad (2)$$

V_L , V_E , and V_I in Eq. 1 are reversal potentials of leak, excitatory, and inhibitory postsynaptic currents, respectively. τ_{mX} is a membrane time constant. s_j in Eq. 2 is a spike timing of synaptic input from the j -th neuron. The value of $\delta(t - s_j - d_j)$ is 1 only when the sum of the j -th neuron's spike timing and its delay equals to the time t . The spike modulates conductance of the post synaptic neuron in proportion to the connection strength G_{XX} . All the parameters in Eqs. 1 and 2 were set to be the same values in [12] except G_{II} . Originally, $G_{II} = 0.0025$, but we set $G_{II} = 0.0027$ to adjust the firing rates of excitatory and inhibitory neurons.

We implemented a random network in which 10000 excitatory and 2000 inhibitory neurons were connected directly, with conjunctive probabilities of 0.1 for

excitatory neurons and 0.5 for inhibitory neurons. The excitatory-to-excitatory connection strength was decided by the EPSP. The EPSP was designed to follow a lognormal distribution, as shown in Eq. 3.

$$p(x) = \frac{\exp(-(\log x - \mu)^2/2\sigma^2)}{\sqrt{2\pi}\sigma x} \quad (3)$$

2.3 External Input Distribution

We tested the neural responses with an assumption that visual attention modulates input spike sequence to V4. We also assumed that the firing rates of external input followed a lognormal distribution, in order to make it similar to the case of primary auditory cortex where the firing rates are lognormally distributed [14, 15]. The firing rate and variance of external input were determined depending on the attended condition or unattended condition, and then input spike sequences were generated according to the Poisson process in each trial. We call the input explained above as external input distribution.

2.4 Simulation

In order to trigger spontaneous neural activity, we set noisy input at the first 0.1 s of simulation. A confirmation period followed for 2.4 s to confirm spontaneous activity. In the first SHUFFLE from 2.5 to 3.0 s, weak external input distribution was generated, and then, the ordinary external input distribution was set from 3.0 to 4.0 s as PAUSE. Again, external input distribution became weak from 4.0 to 4.5 s in the second SHUFFLE. Here, we set firing rate and variance of the external input distribution during PAUSE to be (10.0 Hz, 10.0) in the unattended condition and (10.0 Hz, 140.0) in the attended condition. In SHUFFLE, the firing rate and Fano factor of the input were set to be (1.0 Hz, 1.0). PAUSE and two SHUFFLE periods were used for analysis.

3 Results

3.1 Firing Rate and Fano Factor

Fig.2 shows the simulated neural responses under the assumption that the variance of external input distribution increases for the attended condition relative to the unattended one. Because most of the BS and NS neurons anatomically correspond to excitatory pyramidal neurons and inhibitory interneurons, respectively [9–11], excitatory and inhibitory neurons were used in the simulation, and eventually both showed increased firing rates by the input. The firing rates became much larger in the attended condition than the unattended condition (Fig.2 A and B), and the Fano factor became lower in the attended condition than the unattended condition (Fig.2 C and D).

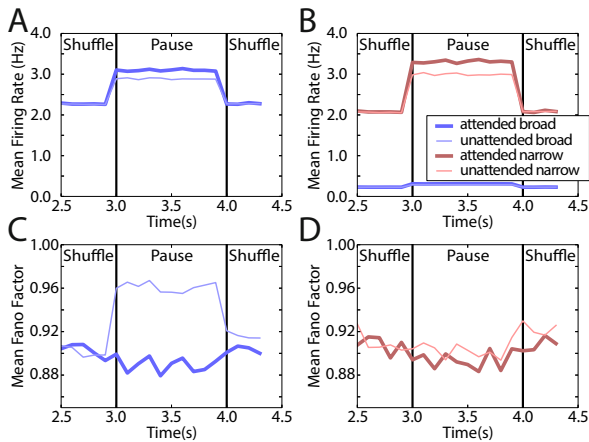


Fig. 2. Simulated neural responses for the external input distribution. A and B: averaged firing rates of BS (blue) and NS (red) neurons for the attended (dark red, dark blue) and unattended (light red, light blue) conditions. C and D: averaged Fano factors of BS and NS neurons for the attended and unattended conditions.

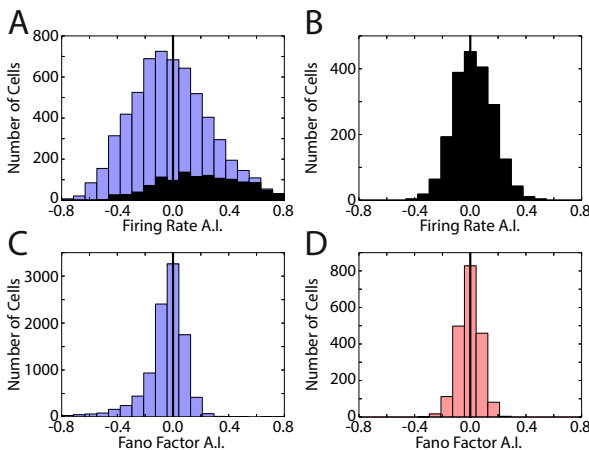


Fig. 3. Distribution of attention index for BS (blue) and NS (red) neurons. A and B: attention index for firing rate. C and D: attention index for Fano factor. Significantly modulated neurons are indicated in black.

3.2 Attention Index

We analyzed the firing rate and the Fano factor of individual neurons during PAUSE using AI. Firing rate AI of the excitatory neurons had larger variance than those of the inhibitory neurons, and Fano factor AI was lower in the attended condition than the unattended condition (Fig.3). Similar to Fig.1 E and F, significantly modulated neurons were observed for the firing rate AI.

3.3 Input-Output Relationship

We then analyzed the relationship between the variance of the external input distribution and the neural responses. As shown in Fig.4, increase in firing rate and decrease in Fano factor were observed according to the variance of the input.

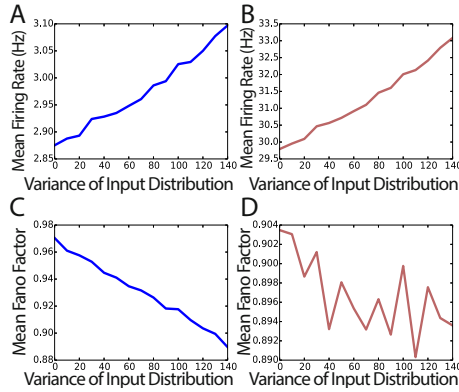


Fig. 4. Fluctuations of firing rate and Fano factor as a function of the variance of the external input distribution. A and B: fluctuations of firing rate of BS (blue) and NS (red) neurons. C and D: fluctuations of Fano factor of BS (blue) and NS (red) neurons.

4 Discussion

We simulated the attention modulation in V4 using lognormally distributed external input, under the assumption that attention modulates the variance of external input distribution. The simulated results were confirmed not only by the global trend of firing rate and Fano factor (Fig.2) but also by the individual trend of attention index (Fig.3).

According to Mitchell et al. [5], individual Fano factors for most of the NS and BS neurons became lower in the attended condition than the unattended condition, as shown in Fig.1 F. Therefore, the averaged Fano factor showed the same trend (Fig.1 C and D). Consistent with Mitchell et al., the simulation results showed that the Fano factor and the Fano factor AI became lower in the attended condition than the unattended condition (Fig.2 C and D, Fig.3 C and D, respectively). Moreover, in Mitchell et al., while individual firing rates of NS and some BS neurons became larger in the attended condition, those of particular BS neurons became significantly lower even in the attended condition (Fig.1 E). In this study, the firing rates became larger in the attended condition than the unattended condition (Fig.2 A and B), and the firing rate AI of the excitatory neurons had larger variance than those of the inhibitory neurons (Fig.3 A and B), which are also consistent with Mitchell et al. Significantly modulated neurons in firing rate AI confirm that the attention modulation variability in excitatory

neurons was not caused by noise. Consequently, we succeeded to reproduce the physiological phenomena occurred in V4 for visual attention in the neural circuit.

We observed increase in firing rate and decrease in Fano factor according to the variance of the input. This relationship indicates that the variance change in the external input distribution can be one reasonable explanation for visual attention modulation in V4. If the variance of lognormal distribution increases, most of that input's firing rates become low, and a few input's firing rates become high. From the result about the increase in the firing rates of some neurons and the decrease in Fano factor in the attended condition, we have one possibility that a computation of these neurons in the pre-network might improve signal-to-noise(S/N) ratio. In recent attention study, it is focused on not only firing rate or Fano factor, but also noise correlation that is the pair-wise correlation between two neuron's spike count. It is revealed that noise correlation is significantly modulated by attention [16, 17], and the performance of orientation change detection task improved when noise correlation was low [17]. Moreover, about 80 percent of the stimulus discriminability could be explained by the noise correlation in the simulation study based on physiological data [17]. Noise correlation can be treated as the reciprocal of the independence of neuronal activity, because it is a pair-wise correlation. For these reasons, it is plausible that the computation of S/N ratio to the stimulus is modulated by attention. However, specific hardware which can compute the S/N ratio to arbitrary feature or objects has not been cleared yet. Further studies are needed to the topic.

5 Conclusion

We simulated the attention modulation in V4 using lognormally distributed external input delivered to the spontaneously spiking neural model. Under the assumption that the visual attention is achieved by an increase in variance of external input distribution, both increase in firing rate and decrease in Fano factor were observed, consistent with a physiological report. These results suggest that we succeeded to computationally reproduce the attention modulation in V4 and that the modulation is caused by improved signal-to-noise ratio for a target stimulus. In the future, we are planning to analyze the relationship between the neural network structure and the signal-to-noise ratio of activity, in order to clarify how the signal-to-noise ratio is related to visual attention.

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