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A hierarchical chaotic neural network model for multistable binocular rivalry

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Abstract—Binocular rivalry is perceptual alternation that occurs when different images are presented to the two eyes. Despite efforts of many neuroscientists, the mechanism of binocular rivalry still remains unclear. In multistable binocular rivalry, which is a special case of binocular rivalry, it is known that the perceptual alternation between paired patterns is more frequent than that between unpaired patterns. This result suggests that perceptual transition in binocular rivalry is not a simply random process and the memories stored in the brain play an important role for the perceptual transition. In this paper, we propose a hierarchical chaotic neural network model for multistable binocular rivalry and show that our model reproduces some characteristic properties in multistable binocular rivalry.

1. Introduction

In cognitive science, one of the interesting topics is subjective visual perception. Binocular rivalry is the famous phenomenon used in this topic. When two different visual stimuli are presented to one's each eye, he/she percepts not the mixed single image but the each presented images alternately[1].

In most cases, subjective perception mainly alternates between two competing images. However, some stimulus sets can induce more than two plausible interpretations. For example, when upright triangle is presented to right eye and inverted triangle to left eye, subjective perception alternates among four patterns; upright triangle (presented to right eye), inverted triangle (presented to left eye), left-skewed parallelogram (mixture of right half of right eye and left half of left eye), right-skewed parallelogram (mixture of left half of right eye and right half of left eye) (Figure 1). It is known that the brain can combine nonoverlapping parts of two monocular images, for example the right half of the image presented one eye and the left half of another eye, to form one coherent perception[2]. This phenomenon, called interocular grouping, enables subjects to perceive four images, i.e., two monocular images and two interocular images.

In contrast with bistable binocular rivalry, there has been few works on the dynamics of multistable binocular rivalry. Suzuki and Grabowecky reported some interesting properties in multistable binocular rivalry [3]. In this study, they used stimulus sets inducing four stable perceptions by using interocular grouping and these four patterns are clustered into two related pairs in some stimulus sets. One important result is that when the stimulus sets which have related pairs were presented to subjects, the subjective perceptions did not change randomly and these perceptual alternations were more frequent between paired patterns than between unpaired patterns. This bias of transition probability is independent of whether the perceptual images are monocular images or interocular images. However, when the used stimulus sets didn't have related pairs, such differences in the transition probability disappeared. .They accounted for these results in terms of attractor diagram. Perceptual states of related pairs were separated by lower potential barriers. Therefore the transition probabilities between related pairs were higher than that between unrelated shapes.

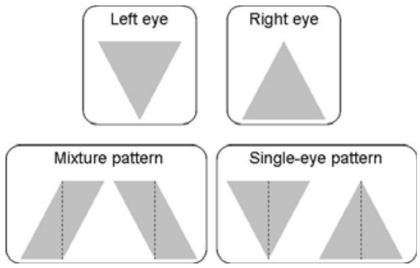

Figure 1: Example of a stimulus used in multistable binocular rivalry.

The brain areas forming the setting of binocular rivalry is one of main issues [4]. In one view point, binocular rivalry arises from interocular competition in lower level visual area (V1, LGN). In another view point, higher level visual areas contribute to binocular rivalry and what this phenomenon reflects is not competitions between the eye stimuli however those between the object representations. Although many scientists have worked vigorously to address this problem, the brain areas playing a critical role for binocular rivalry remain inconclusive.

The mechanism of the perceptual switching is also debated. It is known that the dynamics of each perceptual dominance duration is well fitted by gamma distribution or lognormal distribution [5]. Because the timing of perceptual switching is apparently random and the length of a particular dominance duration cannot be predicted by the preceding dynamics of perceptual alternation, the mechanism underlying binocular rivalry is supposed to be a stochastic process. However, the paper of Suzuki and Grabowecky implies that the memories in the brain have an effect on the dynamics of binocular rivalry and the mechanism of binocular rivalry is not simply random process.

In this paper, we present a model for multistable binocular rivalry, which consists of chaotic neurons and yields some chaotic attractors corresponding to each perceptual state. The state of this network wanders from attractor to attractor without external noise. The distribution of durations which network state remains around each attractor is well fitted by lognormal distribution and some other properties obtained by psychological experiments are also reproduced. In section 2, we will describe two theoretical topics based on our model and explain our model in detail. Simulation results will be presented in section3 and we will conclude in section 4.

2. Model framework

In this section, we explain our proposed model for multistable binocular rivalry. This model is based on two ideas: one is chaotic neural network model and the other is predictive coding model. The former is an artificial neural network model composed of chaotic neurons which show chaotic dynamics in certain parameters and the latter is a model of visual processing which interprets a brain function to predict external world. Firstly we describe these two basic ideas, and then, we explain our proposed model.

2.1. Chaotic neural network model

Chaotic neural network model is an artificial neural network model composed of chaotic neurons [6]. Chaotic neuron model is one of single neuron models which shows chaotic dynamics and described as

$$x_i(t+1) = f\left[\sum_{j=1}^{M} v_{ij}\sum_{d=0}^{t} k_e^d A_j(t-d) + \sum_{j=1}^{N} w_{ij}\sum_{d=0}^{t} k_f^d x_j(t-d) - \alpha\sum_{d=0}^{t} k_r^d g\{x_i(t-d)\} - \theta_i\right],$$

where $x_i(t)$ is the ith neuron output with an analogue value between 0 and 1 at the discrete time steps. f and g are the output function and the refractory function respectively. $A(t)$ is the external stimulation at the time t. v_{ij} and w_{ij} are synaptic weights to the i th neuron from the j th external input and from j th internal neuron respectively. k_e, k_f, k_r are the decay parameters for the external inputs, the recurrent connection, and the refractoriness respectively, and α and Θ are the refractory scaling parameter and the threshold respectively. Using the appropriate parameters, this network does not remain particular stable point however nonperiodically retrieves various patterns embedded in this network one after another.

2.2. Predictive coding model

Predictive coding model is a model of visual processing which interprets a brain function to predict external world [7]. In this model, feedback projections carry predictions of lower level neural activity from a higher level to a lower level, whereas feedforward projections carry residual errors between the predictions and actual neural activity from a lower level to a higher level. These errors are used by the predictive estimator at each level to correct its current estimate of the input signal and generate the next prediction.

2.3. Proposed model

We propose a hierarchical chaotic neural network model based on foregoing two models for multistable binocular rivalry. This model is composed of two layers: Lower layer, which is assumed to lower visual area, and higher layer, which is assumed to higher visual layer. For replicating binocular rivalry condition, we prepare two input layers which correspond to right eye and left eye, and lower layer is connected with both two input layers. For inter layer connections, we adopt the idea of predictive coding model: feedback connections carry predictions and feedforward connections convey residual errors calculated from predictions and actual neural activities (Figure 2).

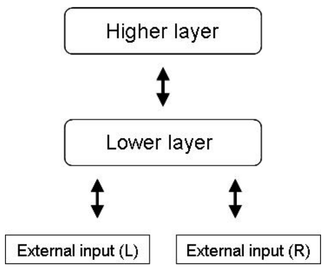

Figure 2: Structure of proposed model.

The dynamics of the lower layer neurons $\boldsymbol{x}_1$ as follows:

$$\begin{aligned}
\boldsymbol{x}_1(t+1) &= f\{\boldsymbol{y}_{\mathrm{e}}(t+1)+\boldsymbol{y}_{\mathrm{i}}(t+1)+\boldsymbol{y}_{\mathrm{r}}(t+1)+\boldsymbol{y}_{\mathrm{fb}}(t+1)\},\\
\boldsymbol{y}_{\mathrm{e}}(t+1) &= k_{\mathrm{e}}\boldsymbol{y}_{\mathrm{e}}(t)+\alpha_{\mathrm{e}}\mathrm{U}_1^{-1}(\boldsymbol{E}-\mathrm{U}_1\boldsymbol{x}_1(t)),\\
\boldsymbol{y}_{\mathrm{fb}}(t+1) &= k_{\mathrm{fb}}\boldsymbol{y}_{\mathrm{fb}}(t)+\alpha_{\mathrm{fb}}(\mathrm{U}_2\boldsymbol{x}_2(t)-\boldsymbol{x}_1(t)),\\
\boldsymbol{y}_{\mathrm{i}}(t+1) &= k_{\mathrm{i}}\boldsymbol{y}_{\mathrm{i}}(t)+\alpha_{\mathrm{i}}\mathrm{W}_1\boldsymbol{x}_1(t),\\
\boldsymbol{y}_{\mathrm{r}}(t+1) &= k_{\mathrm{r}}\boldsymbol{y}_{\mathrm{r}}(t)-\alpha_{\mathrm{r}}\boldsymbol{x}_1(t)-\theta(1-k_{\mathrm{r}}),
\end{aligned}$$

and the higher layer neurons $\boldsymbol{x}_2$ are described as follows:

$$\begin{aligned}
\boldsymbol{x}_2(t+1) &= f\{z_{\mathrm{ff}}(t+1) + z_{\mathrm{i}}(t+1) + z_{\mathrm{r}}(t+1)\},\\
z_{\mathrm{ff}}(t+1) &= k_{\mathrm{ff}} z_{\mathrm{ff}}(t) + \beta_{\mathrm{ff}} \mathrm{U}_2^{-1}(\boldsymbol{x}_1(t) - \mathrm{U}_2\boldsymbol{x}_2(t)),\\
z_{\mathrm{i}}(t+1) &= k_{\mathrm{i}} z_{\mathrm{i}}(t) + \beta_{\mathrm{i}} \mathrm{W}_2 \boldsymbol{x}_2(t),\\
z_{\mathrm{r}}(t+1) &= k_{\mathrm{r}} z_{\mathrm{r}}(t) - \beta_{\mathrm{r}} \boldsymbol{x}_2(t) - \theta(1-k_{\mathrm{r}}),
\end{aligned}$$

where each $\boldsymbol{y}$ and $\boldsymbol{z}$ is the internal state term of the lower layer neurons and the higher layer neurons respectively. Suffixes e, fb, i, r, and ff mean external inputs, feedback input, intrinsic connection, refractoriness, and feedforward input respectively. Each α and β is the scaling parameter, and each k denotes the decay parameter respectively. Each U and W are the synaptic weights of the interlayer connections and the intrinsic connections respectively. $\boldsymbol{E}$ is the external input vector.

For the output function f, we use the logistic function represented by

$$f(y) = \frac{1}{1+\exp(-y/\epsilon)},$$

where ϵ is a parameter for the steepness of the function.

3. Simulation results

We considered a simple case of multistable binocular rivalry as figure 1. Four patterns were used for input images and these are composed of two right visual field images and two left visual field images. Accordingly, we used four binary patterns $\boldsymbol{E}_i$ $(i = 1,2,3,4)$ which were composed of four orthogonal vectors ($\boldsymbol{R}_1$, $\boldsymbol{R}_2$, $\boldsymbol{L}_1$, $\boldsymbol{L}_2$) for external input vectors.

$$\boldsymbol{E}_1 = \begin{pmatrix} \boldsymbol{L}_1 \\ \boldsymbol{R}_1 \end{pmatrix},\ \boldsymbol{E}_2 = \begin{pmatrix} \boldsymbol{L}_2 \\ \boldsymbol{R}_2 \end{pmatrix},\ \boldsymbol{E}_3 = \begin{pmatrix} \boldsymbol{L}_1 \\ \boldsymbol{R}_2 \end{pmatrix},\ \boldsymbol{E}_4 = \begin{pmatrix} \boldsymbol{L}_2 \\ \boldsymbol{R}_1 \end{pmatrix}.$$

The intrinsic connections W_1 and W_2 are determined according to the following symmetric auto-associative matrix of stored patterns:

$$\begin{aligned}
\mathrm{W}_1 &= \frac{1}{M}\sum_{p=1}^{M}(2\boldsymbol{A}_p - \mathbf{1})(2\boldsymbol{A}_p - \mathbf{1})^{-1},\\
\mathrm{W}_2 &= \frac{1}{N}\sum_{p=1}^{N}(2\boldsymbol{B}_p - \mathbf{1})(2\boldsymbol{B}_p - \mathbf{1})^{-1},
\end{aligned}$$

where $\boldsymbol{A}_p$ and $\boldsymbol{B}_p$ are the p th stored pattern in the lower layer and the higher layer respectively, and $\mathbf{1}$ indicates a vector whose components is all 1. M and N are the number of stored patterns in the lower layer and the higher layer respectively. In this simulation, $M = 4$ and $N = 2$.

The lower layer stores four binary patterns $\boldsymbol{A}_i$ $(i = 1,2,3,4)$ and the higher layer stores two binary patterns $\boldsymbol{B}_i$ $(i = 1,2)$. We assumed that the network state of the lower layer $\boldsymbol{A}_i$ corresponds to perceptual state of external input $\boldsymbol{E}_i$. The synaptic weight of the interlayer connections between the input layer and the lower layer U_1 is defined as follows:

$$\mathrm{U}_1 = \frac{1}{M}\sum_{p=1}^{M}(2\boldsymbol{E}_p - \mathbf{1})(2\boldsymbol{A}_p - \mathbf{1})^{-1}.$$

On the other hand, the higher layer encodes the information of relationships among the lower layer memory patterns. In this simulation, $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ belong to one group ($\boldsymbol{B}_1$) and $\boldsymbol{A}_3$ and $\boldsymbol{A}_4$ belong to the other group ($\boldsymbol{B}_2$). The synaptic weight of the interlayer connections between the lower layer and the higher layer U_2 is determined by following equation:

$$\begin{aligned}
\mathrm{U}_2 = \frac{1}{N}\sum_{p=1}^{N} \Big\{ &(2\boldsymbol{A}_{2p-1} - \mathbf{1})(2\boldsymbol{B}_p - \mathbf{1})^{-1}\\
&+ (2\boldsymbol{A}_{2p} - \mathbf{1})(2\boldsymbol{B}_p - \mathbf{1})^{-1} \Big\}.
\end{aligned}$$

The number of neurons in the lower layer m is 16 and that of the the higher layer n is 4. Parameter values are fixed to following values, i.e., $k_e = k_{fb} = k_{ff} = 0.01$, $k_i = 0.01$, $k_r = 0.96$, $\alpha_e = 0.01$, $\alpha_{fb} = 0.19$, $\alpha_i = 0.22$, $\alpha_r = 0.009$, $\beta_{ff} = 0.01$, $\beta_i = 0.14$, $\beta_r = 0.009$, $\theta = 0$ and $\epsilon = 0.015$.

3.1. Multistable binocular rivalry

When $\boldsymbol{E}_1$ and $\boldsymbol{E}_2$ were used as external input, the network shows a nonperiodic transient behavior. For evaluating the network state, we define the similarities of the network state to each memory pattern as follows,

$$\begin{aligned}
s_1^{(p)}(t) &= \frac{1}{m}(2\boldsymbol{A}_p - \mathbf{1})^{-1}(2\boldsymbol{x}_1(t) - \mathbf{1}),\\
s_2^{(p)}(t) &= \frac{1}{n}(2\boldsymbol{B}_p - \mathbf{1})^{-1}(2\boldsymbol{x}_2(t) - \mathbf{1}).
\end{aligned}$$

Figure 3 shows a typical time course of $s_1^{(p)}(t)$. We can see that the network state of lower layer transits among

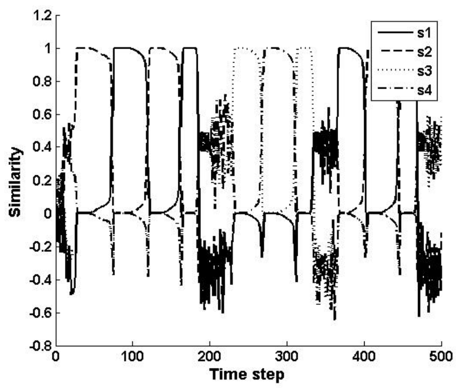

Figure 3: Typical time course of $s_1^p(t)$.

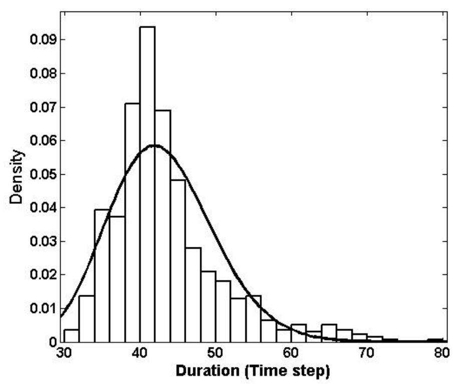

Figure 4: Distribution of dominance durations.

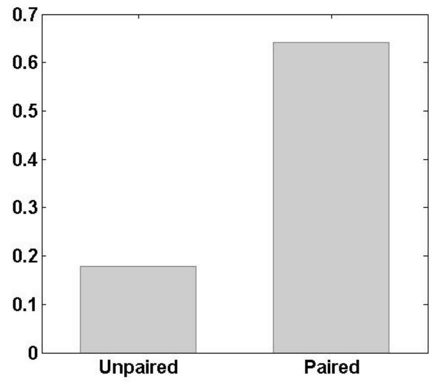

Figure 5: Relative transition probabilities.

memory patterns. A histogram of dominance durations of the lower layer is shown in Figure 4. It appears to be unimodal and skewed with a long tail. The solid line is gamma distribution with parameters $k = 38.7308$ and $\theta = 1.1091$, where the gamma distributions $f(x) = x^{k-1}/\Gamma(k)\theta^k \cdot \exp(-x/\theta)$. This shape of the histogram is consistent with experimental results.

In the lower layer, it is noted that the transitions between paired memory patterns (i.e. between $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$, and between $\boldsymbol{A}_3$ and $\boldsymbol{A}_4$) occur more frequently than that between non paired memory patterns (e.g. between $\boldsymbol{A}_1$ $\boldsymbol{A}_3$). For further analyzing, we computed relative transition probabilities p_r. p_r is defined by following equation,

$$p_r(A|B) = \frac{p(A|B)}{p(A|B) + p(A|C) + p(A|D)},$$

where $p(A|B)$ is the transition probability from patten B to pattern A. p_r should be 1/3 if there was no bias in transition probabilities. For simplicity, we sort p_r into two groups: one is the relative transition probabilities of paired pattern transitions ($p_r^{(paired)}$) and the other is that of unpaired pattern transitions ($p_r^{(unpaired)}$). $p_r^{(paired)}$ is a average of $p_r(\boldsymbol{A}_1|\boldsymbol{A}_2)$, $p_r(\boldsymbol{A}_2|\boldsymbol{A}_1)$, $p_r(\boldsymbol{A}_3|\boldsymbol{A}_4)$ and $p_r(\boldsymbol{A}_4|\boldsymbol{A}_3)$. $p_{(unpaired)}$ is a average of all p_r other than above . From Figure 5, we can see that $p_r^{(paired)}$ is larger than 1/3. This bias of transition probability means that alternations between paired patterns are more frequent than that between unpaired patterns.

4. Conclusion

In this paper, we have proposed a hierarchical chaotic neural network model for multistable binocular rivalry. This model reproduces some characteristic properties in multistable binocular rivalry, i.e., the shape of the dominance duration histogram which is well fitted by gamma distribution function and the bias of relative transition probabilities. These results suggest that the chaotic neurodynamics is one of potential candidates of the mechanism of binocular rivalry.

Acknowledgments

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