The Sixteenth International Symposium on Artificial Life and Robotics 2011 (AROB 16th '11),
B-Con Plaza, Beppu,Oita, Japan, January 27-29, 2011

A Neural Network Model for Categorical Effects in Color Memory

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***Abstract*:** Human color perception is categorical. Previous experimental studies have shown that the color category has profound effects on cortical neural responses, perceptual color discrimination and color memory. However, existing theoretical studies are not enough to provide an inclusive model accounting for those categorical effects in color perception and memory. In this study, we propose a computational model for categorical color processing, where the color memory is represented by a population of color selective neurons in cortex. Our model reproduces the characteristics of color memory reported in the previous experimental studies. Furthermore, it explains the properties of neurons in IT cortex, which change the activity depending on whether the task demands is color categorization or discrimination. This study suggests that perceptual biases found in color processing and task-dependent modulations of neural responses may be explained as a natural consequence of statistically optimal estimation.

Keywords: color memory, categorical color, population coding

I. INTRODUCTION

We perceive millions of colors based on the spectrum of incident light flowing into our eyes. Previous studies show that there are two different ways in how we see colors in spectral space: to look closely or to look as groups. Recognizing very slight differences between colors is called color discrimination. On the other hand, organizing colors within a certain color region into one group is called categorical color perception. Discrimination and categorization are considered as two different functions in color perception.

Psychophysical studies have shown the categorical effects on color discrimination. Harnad (1987) reported that discrimination was better for colors straddling the category boundary than for colors within the same category. Furthermore, considering time factor, color memory is also involved. Perez-Carpinell et al. (1998) showed the mean difference between test color and recalled color increases with the delay time. According to Heider(1972), focal colors (colors at categorical center) are remembered more accurately than non-focal colors.

fMRI and electrophysiological studies suggest that the visual cortical areas subsequent to area V4 play important roles in higher order functions of color vision including categorization and discrimination. Koida et al. (2007) investigated the responses of color-selective neurons in the inferior temporal (IT) cortex of monkeys during making a categorical judgment or a fine discrimination of colors. They found the activity of many IT color-selective neurons differed depending upon the task. Some IT neurons showed stronger activity in the categorization task or in the discrimination task in response to the same color stimulus.

In spite of these clear evidences that color discrimination, color categorization and color memory are related to each other, there is no inclusive model that account for how our brains fulfill each of these functions depending on the situation. In the present study, we propose a computational model that takes into account the categorical effects in color perception and memory, assuming that color selective neurons in cortex express colors in memory. In particular, our model reproduces neural activities of color-selective neurons in the IT cortex during categorical judgment and discrimination, and the categorical effects in color memory.

II. COLOR PERCEPTION MODEL

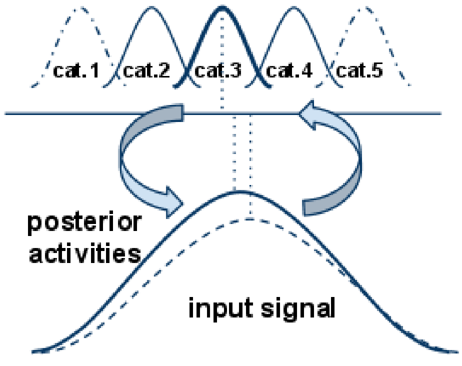

Fig.1. A schematic diagram of the proposed model

Our model explains categorical effects in color perception through the interactions between hue-selective neurons and category-selective neurons. We assume a hue space of one dimension as a color space. The model is summarized in Fig.1.

We assume two groups of color-coding neurons: the first group ('hue-selective neurons') in which the neuronal preferred hue is homogeneously distributed, and the second group ('category-selective neurons') in which the distribution of hue preference is concentrated around some points, which we call 'category center' in this study.

Each hue-selective neuron receives the input signal from earlier processing stages. The strength of the input signal is expressed as a function of the difference between presented hue θ and ith neuron's preferred hue θ_i:

$$\lambda_i(\theta) = f(\theta-\theta_i) = g \cdot e^{k\cos(\theta-\theta_i)} \tag{1}$$

where we used the von-Mises (circular Gaussian) function for the hue selectivity; g is a parameter to control the response gain,. When there is no other input to those neurons, we assume that the neuronal spikes are generated with the following Poisson process:

$$P(r_i \mid \theta) = \frac{(\lambda_i T)^{r_i T}}{(r_i T)!} e^{\lambda_i T} \tag{2}$$

where r_i is the firing rate in one trial; T is the observation duration. The categorical decoding θ^c_k is the hue of kth category center

$$\ln P(\{r_i\} \mid \theta^c_k) = T\sum_i r_i \ln f(\theta^c_k - \theta_i) + const. \tag{3}$$

where we used the fact that the summation $\Sigma_i f(\theta-\theta_i)$ is independent of θ when the neuronal preferred hues are homogeneously distributed. Equation (3) means that the log likelihood of hue category can be calculated as a weighted sum of the hue-selective neurons' activities (the first term) (Jazayeri et al., 2006). In the present model, we hypothesize that the category-selective neurons receive the read-out signals from the hue-selective neurons as follows:

$$a^c_k = \sum_i r_i \ln f(\theta^c_k - \theta_i) \tag{4}$$

By comparing a^c_k for various hue category θ^c_k, we can estimate which category is the most likely to generate the color of visual input. This means that the maximum likelihood estimation of input hue category can be implemented by a winner-take-all process among the category-selective neurons.

Now we consider estimating the hue presented at time t+1 based on the knowledge of hue at time t. Given the assumption that the hue presented in future is likely to be generated from the same category as the present one, the posterior probability is expressed with the Bayes' formula as follows:

$$P(\theta^{t+1} \mid \{r_i^{t+1}\}) \propto P(\{r_i^{t+1}\} \mid \theta^{t+1}) P(\theta^{t+1}) \tag{5}$$

We propose that the information of the prior probability distribution $P(\theta_i^{\ t+1})$ is given by the top-down signal from k-th category-selective neuron to ith hue-selective neuron: $f(\theta^c_k - \theta_i)$. For Poisson-like spike statistics, combining process of two probability distributions is achieved by a simple linear summation of two population activities (Ma et al., 2006). In the present study, we propose that the likelihood and the prior is iteratively recombined through following recurrence formula:

$$\lambda_i(\theta^{t+1}) = \alpha f(\theta^{t+1} - \theta_i) + \beta f(\theta^{c,t}_k - \theta_i) \tag{6}$$

where α and β control the combining ratio. In discrimination task, the parameter β is set to a smaller value than in categorization task. In color memory task, the iteration of Eq. (6) is continued for the length of memory duration. For all of the simulations, g = 1, k = 1, T = 1, α = 1, β = 1, number of category = 2 and number of hue-selective neurons = 2000.

III. RESULTS

1. Categorical effect on Color Memory

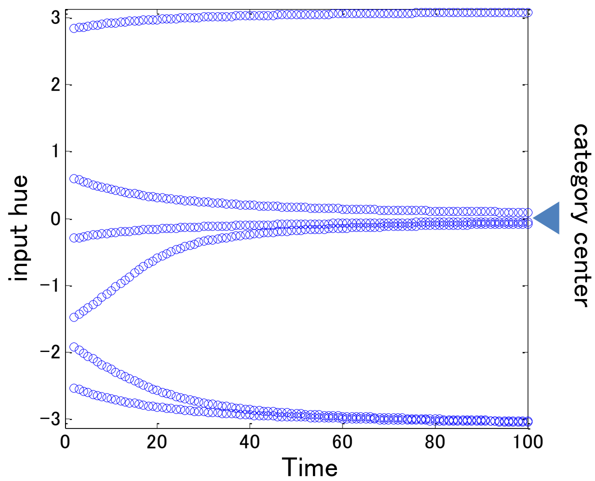

Fig.2. Temporal evolution of the cortical hue representation during the color memory task. We plotted the preferred hue of the neuron that showed the peak activity in the population. The horizontal axis indicates the memory duration. The results for four example initial hues are shown.

Figure 2 shows the temporal evolution of hue values in color memory task. Here, the preferred hue of hue-selective neuron that showed the maximum magnitudes at each time is plotted. Values at time 0 indicates the input hue presented at the initial point of memory task; Each hue-selective neuron is activated responding to the hue input at first. After time 0, hue selective neurons received only the top-down signals from category-selective neurons, and the input signals were set to zero. When the memory duration evolved, the represented hues approached to the nearest category center.

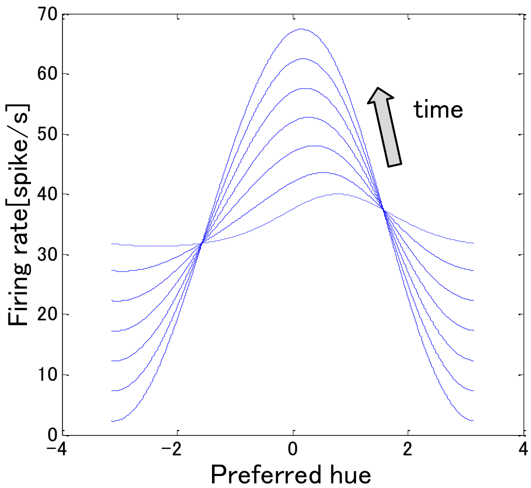

Fig.3 Temporal activity change of hue selective neurons in the color memory task. Horizontal axis denotes the preferred hue of each neuron. Each solid line shows a snapshot of the activities of hue-selective neurons, and dashed line indicates the activity induced by an input signal.

Figure 3 shows the snapshots of the activities of hue-selective neurons, which evolved during the memory task. The peak of the activities distribution of the hue-selective neurons shifts toward the nearest category center. The maximum value of firing rate increases with time.

As it can be considered that the hue centers in the model correspond to the focal colors, these results agree with the characteristics of the results reported by Heider (1972). When input hue is away from each hue center, the model also reproduces the temporal increase in the difference between memory color and initially presented color (Perez-Carpinell et al., 1998).

2. Color categorization and color discrimination

We next investigated how the present model can be related to the response properties of visual neurons in the different task demands of color categorization and discrimination. We simulated the neuronal responses to 11 sample colors (the horizontal axis in Fig.4) which spread on the axis from red to green. Figure 4 shows the activities of a greenish-preferred neuron. The horizontal axis indicates 11 sample colors. In Fig.4, the activity of a hue-selective neuron is shown. Our model reproduces neural activities of color-selective neurons in the IT cortex during categorical judgment and discrimination (Koida et al. 2007).

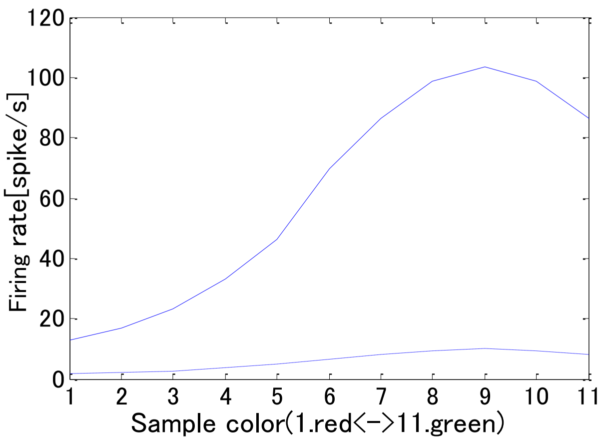

Fig.4 Responses of a hue-selective neuron during ca tegorization (solid line) and discrimination (dashed l ine).

IV. DISCUSSION

Our model reproduces the characteristics found in the previous experimental studies and provides an inclusive explanation for some of the phenomenon concerning categorical color perception, color discrimination and color memory. From Bayesian viewpoint, the neural response properties in IT cortex can be explained as a natural consequence of statistically optimal estimation. This theoretical framework is possibly applied to similar phenomena found in other cortical area involved in different sensory or feature modalities, such as audition, visual motion or face expression.

We assumed that the main categorical effects are elicited by top-down signals from category selective neurons in the response to the input from hue-selective neurons. In the combining process of input and top-down signals, we applied a simple static linear summation for a purpose of conciseness. Further studies may cover a saturation and adaptation of neuronal responses or weight varying with time.

The present model considers only one-dimensional hue shift with the duration between memory and recall, though shifts of color saturation and lightness are also reported in psychophysical studies of color memory. These factors should be considered in an extension of the current model.

Another topic to be considered is the neurobiological substrate of categorical computation. Although Fig. 4 only depicts the activities of hue-selective neuron, we found that the corresponding category-selective neuron also showed the similar pattern. It can be supposed that the category-preferred neurons in Koida et al. (2007) correspond approximately to the hue-selective neurons in this model, category-preferred neurons also alike.

V. CONCLUSION

We proposed a computational model for higher order mechanisms of color perception. Our model reproduces the characteristics of categorical effects including color memory reported in the previous experimental studies. From the perspective of statistically optimal estimation, this study provides one possible explanation of the relation among categorical color perception, color discrimination and color memory in the higher visual cortex in the brain.

ACKNOWLEDGEMENT

This research is supported in part by the Japan Society for the Promotion of Science (JSPS) through its "Funding Program for World-Leading Innovative R&D on Science and Technology (FIRST Program)."

REFERENCES

[1] K. Koida & H. Komatsu (2007), "Effects of task demands on the responses of color-selective neurons in the inferior temporal cortex." *Nature Neuroscience*. 10(1) 108-116

[2] E. R. Heider (1972), "Universals in color naming and memory." *J. Exp. Psychol*. 93, 10-20

[3] S. Harnad (1987), "Category induction and representation." In S. Harnad (Ed.), Categorical perception: *The Groundwork of Cognition*. 535-565. Cambridge: Cambridge University Press.

[4] J. Perez-Carpinell, R. Baldovı et al. (1998) "Color Memory Matching: Time Effect and Other Factors." *COLOR research and application*, 23(4) 234-347

[5] M. Jazayeri & J. A. Movshon (2006) "Optimal representation of sensory information by neural populations." *Nature Neuroscience*, 9(5):690-696.

[6] W. J. Ma, J. M. Beck et al. (2006) "Bayesian inference with probabilistic population codes." *Nature Neuroscience*, 9:1432-1438