A neural network model of the olfactory system of mice: Simulated the tendency of attention behavior

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Abstract

The demands for odor processing apparatuses have been increasing in fragrance or food industries. However, odors are extremely high dimensional information composed a combination from tens thousands of different odorant molecules, and thus requires vast amounts of computation. Therefore, it is considered learning from a living nose would be an efficient approach. From the odor discrimination experiments, it was found that mice have a feature extraction ability called Attention by which they could focus on the important odorants for odor discrimination. In this paper we propose a neural network model approximated to actual number of neurons and the structure of olfactory system. Simulation experiments of the proposed model were implemented based on the odor discrimination experiments on the living mice. From the simulation results of the model, we confirmed not only the proposed model had ability of Attention, but also the tendency of Attention was consistent with the living mice.

1 Introduction

Recently, the demands for odor processing apparatuses have been increasing in fragrance or food industries. However, odors are extremely high dimensional information composed a combination from tens thousands of different odorant molecules. Therefore, odor information requires vast amounts of computation for discrimination or feature extraction [1]. Thus far, to reduce its dimension, the dimension of most odor discriminating apparatuses were specialized for particular odor such as the electronic nose for banana ripeness developed by Llobet et al [2]. On the other hand, most animals discriminate a number of different odors for survival. Therefore, learning from the olfactory system of a living nose would be one of the most efficient and prospective approaches [1, 3].

![Diagram of odor discrimination](https://example.com/diagram.png)

Figure 1: The concept of Attention

Our research group has conducted a series of odor discrimination experiments on mice [4]. First, the mice are trained to select a rewarded odor composed of three kinds of odorants [IA, CI, EB]. Then, they were required to discriminate the odors that contain a part of odorant in odor [IA, CI, EB] such as [IA] or [IA, EB] etc. As a result, we observed most mice had difficulty to distinguish [IA, EB] from [IA, CI, EB]. It implies that the mice made attention on a combination of odorants [IA] and [EB] when they learnt [IA, G, EB] as described in Fig. 1. This mechanism is called Attention. Because making attention on appropriate odorants [4] will enable an efficient dimension reduction or feature extraction, mechanism of Attention is of importance to process high dimensional odor information. So far, Li et al. and Cleland et al. have revealed several feature extraction mechanism of olfactory system, however, mechanism of Attention has yet to be explored. To reveal how the olfactory system process Attention, the signal transduction between neurons must be measured, nevertheless it is beyond current technology to collect enough data. In this paper, we propose a neural network model constructed based on anatomical insight, and try to elucidate the mechanism of Attention through simulation. Further, the simulation results of the proposed model are compared.
with the odor discrimination experiment results of the living mice.

2 The odor discrimination experiments

This section details the series of odor discrimination experiment on mice aimed to reveal Attention [4].

2.1 Methods

The subject of the experiment was water-deprived C57BL/6J mouse. Fig. 2 shows a Y-maze apparatus. In Fig. 2(a), E1 and E2 are the end where odors and water are presented, while S is the end where the mouse are placed at the beginning of each trial. Fig. 2(b) shows a water feeder and a hole for odor emanation located at E1 and E2.

First, odor A and water are presented at either end E1 or E2 randomly so that the mouse is trained to select the end where odor A emanates. Such trials are repeated for 24 times a day until the error rate to drop below 20%. Then, the trained mice are required to discriminate the odor B of which odorants are partly common with the odor A. The odor B is presented at the opposite end to the end where odor A and water are presented. If the mouse were able to discriminate odor A form odor B, they are supposed to choose the end where water and odor A is provided.

This series of experiments was implemented on eight mice. The odor A was a mixture of three kinds of odorants, Isoamyl Acetate (IA), Citral (Ci) and Ethyl Butyl (EB), expressed as [IA, Ci, EB] by the abbreviation of each odorant. The odor B's, such as [EB], [Ci], [IA, EB] etc., were consisted of combinations from those three odorants.

2.2 Results

Fig. 3 shows the averages and standard deviations of error rates obtained from eight mice. The horizontal axis shows the odor Bs ([Ci], [EB], [IA], [EB, IA]), and vertical one shows the error rate.

From Fig. 3, we can find the error rates to [IA], [Ci] or [EB] are about 10 to 15 %, and could be assumed that the mice were able to discriminate [IA, Ci, EB] from those odors. To [IA, EB], in contrast, the error rate is nearly 50 %, which indicates the mice could not discriminate the odors because they were under an either-or situation. This result implies that the mice have made attention on the combination of odorants [IA] and [EB] when they learnt [IA, Ci, EB], and subsequently they could not find the difference between [IA, Ci, EB] and [IA, EB] [4]. From the experiment, it is suggested that the mice would make attention on a part of odorants contained in an odor. This mechanism is called Attention.

3 A model of olfactory system of mice

A neural network model is proposed based on anatomical insights [5, 7, 8]. This section describes the basic structure of olfactory system of mice, the proposed model, and the learning algorithm.

3.1 Structure of olfactory system of mice

Fig. 4 shows the basic structure of olfactory system of mice. The olfactory system is composed of three parts which are receptor neurons, olfactory bulb and piriform cortex. Receptor neurons that bind to specific odorants distributes on the surface of nasal, expressing only one receptor gene among a thousand different genes [9]. As the odorant molecules binded, the recep-
Inhibitory connection

Figure 4: Olfactory system of mice. The activity pattern of glomeruli is cited from literature [10].

Figure 5: A model of the olfactory system in mouse. The PPC layer is consisted of linear neuron models, all layers are consisted of sigmoidal neuron models.

The output \( U_i(t) \) of \( i_{th} \) sigmoidal neuron model or linear neuron model at the time step \( t \) is given by the following equation:

\[
U_i(t) = \frac{1}{1 + \exp(-\theta_i u_i(t) - \epsilon_i)} \quad \text{(Sigmoidal neuron)}
\]

\[
U_i(t) = \alpha u_i(t) - 1 + \sigma_j W_{ij}(t) U_j(t) \quad \text{(Linear neuron)}
\]

where \( \epsilon_i \) is the gradient of sigmoid function, \( \theta_i \) is the threshold value, and \( \alpha \) is a constant gain value. The internal states \( u_i(t) \) of the neuron model is given by the following equation:

\[
u_i(t) = -\alpha u_i(t - 1) + \sigma_j W_{ij}(t) U_j(t)
\]

where \( \alpha \) is the time constant, \( U_j(t) \) is the output of \( j_{th} \) neuron model that is connected to \( i_{th} \) neuron model, and \( W_{ij}(t) \) is the connective weight between \( i_{th} \) and \( j_{th} \) neuron models. The connections between the neuron models in each layer are prepared based on the structure of olfactory system described in Section 3.1.

It is suggested that the interconnections in piriform cortex have a role of pattern complement from retrograded input patterns [7, 12, 6]. For simplification, assuming no noise from input, the interconnections in piriform cortex are neglected in this paper. Further, it is suggested through a simulation by Cleland et al. [6] that the interconnections in olfactory bulb plays an role to normalize the amount of activity within glomeruli. In this paper, since we utilize the glomeruli activity patterns provided by Johnson et al. [10] that are normalized to the normal distribution, the interconnections in the olfactory bulb are assumed to be able to neglected.

The upper side of Fig. 6 shows the activity patterns of glomeruli to monomolecular odorants that are normalized to normal distribution provided by Johnson et al. [10]. The activity patterns are divided into 1805 lattices, and the activity of each lattice is inputted
odors and the reward. The output of each neuron model in the Mitral layer for odor A is assumed to be $M_i^A$, while for odor B $M_i^B$. In addition, considering the odors are identified in the APC layer, the output which indicates the rewarded odor is set to be $A_i^A$, while for unrewarded odor $A_i^B$. To covert the input patterns $M_i^A$ and $M_i^B$ to $A_i^A$ and $A_i^B$ respectively, $W_{ij}^{MA}(t)$ is modulated by the following equation:

$$W_{ij}^{MA}(t+1) = \begin{cases} \alpha_m W_{ij}^{MA}(t) + \beta_m M_i^A(t) A_i^A(t) & \text{(Odor A)} \\ \alpha_m W_{ij}^{MA}(t) + \beta_m M_i^B(t) A_i^B(t) & \text{(Odor B)} \end{cases}$$

(5)

where $\alpha_m$ is the forgetting term and $\beta_m$ the learning rate.

The 2nd phase is to calculate the difference between odor A and odor B by modulation of connective weights $W_{ij}^{AG}(t)$ from the APC layer to the Granule layer.

$$W_{ij}^{AG}(t+1) = \begin{cases} \alpha_g W_{ij}^{AG}(t) + \beta_g M_i^A(t) A_i^B(t) & \text{(Odor A)} \\ \alpha_g W_{ij}^{AG}(t) + \beta_g M_i^B(t) A_i^A(t) & \text{(Odor B)} \end{cases}$$

(6)

In the same way as equation (5), $\alpha_g$ is the forgetting term, and $\beta_g$ the learning rate. When odor A is inputted, the outputs of the APC layer $A_i^A$ are converted to the outputs of the Granule layer $M_i^B$ through $W_{ij}^{AG}$. Similarly, when odor B is inputted, the outputs of the APC layer $A_i^B$ are converted to the outputs of the Granule layer $M_i^A$ through $W_{ij}^{AG}$. Then, the outputs of the Granule layer inhibits the neuron models in the Mitral layer through $W_{ij}^{GM} = -\delta_{ij}$. Consequently, the neuron models in Mitral layer output a activity pattern either $M_i^A - M_i^B$ or $M_i^B - M_i^A$ which represents the difference between two odors.

The 3rd phase extracts the most effective neurons for discrimination. After learning phase 2, it is considered that the neuron models of the Mitral layer with the strongest outputs could emphasize the difference between odor A an odor B. In the proposed model, we assume the connective weights between the Mitral layer and the PPC layer form a competitive system, and the corresponding connective weights are determined according to the competitive system proposed by Amari et al. [14]; these connective weights include self-feedback connective weights $W_{ij}^{MM}$ in the Mitral layer, feedforward connective weights $W_{ij}^{MP}$ from the Mitral layer to the PPC layer, and the feedback connective weights from the PPC layer to the Granule layer. The competitive system extracts a neuron having the greatest output within a certain neuron group in

3.3 The learning algorithm

Most computational functions of the olfactory system have not been revealed clearly. In this paper, the modulation of synaptic plasticity or the signal transduction between the neurons are hypothesized based on related studies [14] and the experimental results of odor discrimination on the mice [4] described in Section 2. Considering the experiment required the mice to discriminate an rewarded odor A and unrewarded odor B, the learning algorithm for the proposed model consists of the following three phases.

In the 1st phase, the connective weights $W_{ij}^{MA}(t)$ from the Mitral layer to the APC layer are modulated to learn the relationship between the inputted
the Mitral layer. In the proposed model, the neurons in the Mitral are randomly divided into 100 groups. Consequently, after the 3rd learning phase, at most 100 neurons should be extracted.

Finally, it is expected that the proposed model could extract the information that expresses the difference between odors, and have importance for odor discrimination.

4 Simulation

In this section, the computer simulations with the proposed model are described. The simulation condition was determined according to the odor discrimination experiment of the living mice. Then, the computer simulation results are compared to that of the living mice described in Section 2.

4.1 Learning of the reward odor

Following the odor discrimination experiment of the living mice, odor [IA, Ci, Eb] and [Air] are inputted to the proposed model alternatively, and the connection weights are adjusted following the learning algorithm described in Section 3.3. The initial values of the connection weights are determined by uniform random values.

Fig. 7(a), (b) shows the outputs of the Glomerular layer when odor [IA, EB, Ci] and odor [Air] are inputted respectively. In this simulation, we assumed the output of odor [Air] for the Glomerular layer to be a constant noise. Fig. 7(c) shows the outputs of the Mitral layer when odor [IA, EB, Ci] is inputted at the time step t. The activity distribution of the neuron models corresponds to the odor bar where red denotes higher activity.

Fig. 7(c) indicates that the activity pattern of the Mitral layer is an enhanced pattern of the Glomerular layer shown in Fig. 7(a) at the initial state (t = 0). After the 1st and 2nd learning phase have completed (t = 10), the activity pattern of the Mitral layer reflects the difference of the patterns shown in Fig. 7(a) and Fig. 7(b). Finally, when the 3rd learning phase has completed (t = 15), the neurons of the Mitral layer with the strongest outputs at t = 10 are extracted as a result of competition (shown in Fig. 7(c)). Consequently, the activated region becomes narrower but the activity has gained stronger through the proposed learning algorithm. Because a part of the inputted pattern on the Glomerular layer has extracted by the Mitral layer, it could be concluded that the proposed model has an ability of feature extraction.

4.2 Comparison with the behavior experiments on mice

To compare the tendency in the feature extraction of simulations and the Attention behavior of the living mice, the simulation results are compared to that of odor discrimination experiments on mice. First, the similar simulation as Subsection 4.1 have implemented on 6 different odors [IA], [EB], [Ci], [IA, EB], [IA, Ci] and [Ci, EB]. The outputs of the Glomerular layer to each odor are shown on the lower side of Fig. 8. The outputs of the Mitral layer after the 3rd learning phase are shown in the middle of Fig. 8. In addition, the overlap rates of each activity pattern of the Mitral layer to that of odor [IA, Ci, EB] are plotted on the top of Fig. 8. The overlap rate is defined as the ratio of the region that both patterns are activated in common against to the total activated region. Further, the error rates obtained from the odor discrimination experiments on the living mice are plotted beside the overlap rates. From Fig. 8, we can find similar tendency between the error rates and the overlap rates;
the higher overlap rate is, the higher the error rate. This result indicates the feature extraction by the proposed learning algorithm is consistent with Attention to an extent.

However, in the case of odor [Ci, EB] and [IA, Ci], the overlap rate differs significantly as compared to the error rates of the living mice. This could be caused by the initial values of the connective weights. Therefore, the simulation result might be able to be improved by taking the average of simulation results over various initial values of the connective weights.

5 Conclusion

In this paper, we proposed a neural network model of olfactory system of mice aimed to explore the algorithm called Attention. The simulation results of the proposed model have a certain consistency with that of the odor discrimination experiments on mice, which indicates that the model has ability similar to Attention.

Having the mice to discriminate the same odors repeatedly, we found the mice could lower the error rate and improve their discrimination ability with changing the tendency of Attention. For the future work, we are planning to investigate the underlying algorithm of the experiment results and improve the proposed model.

Acknowledgements

This work is partially supported by the 21st Century COE Program of JSPS (Japan Society for the Promotion of Science) on Hyper Human Technology toward the 21st Century Industrial Revolution.

The authors would like to thank Dr. Okuhara Keisuke for his biological advise, Dr. Suzuki Michiyo and Mr. Hirono Akira for their editing skill and having always been supportive.

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