A neural network model of the olfactory system of mice: Computer simulation of an attention behavior of mice for some components in an odor

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Abstract

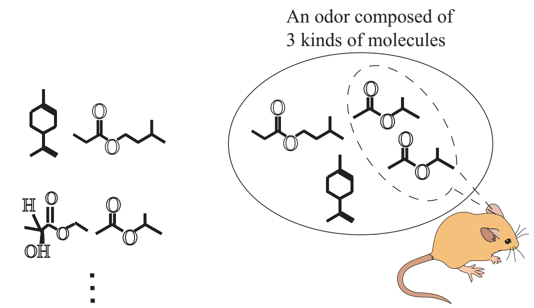
Recently, it was observed that mice could identify an odor by paying attention to only a few components comprising the odor. It was also reported by Nakamura *et al.* [1] that each individual is attracted to different components. This mechanism is called "attention;" however, it has not been completely elucidated.

In this paper, first, we propose a novel artificial neural network model based on the biological structure of an olfactory system. Then, a series of computer simulations of odorant discrimination are performed to confirm the ability of attention of the proposed model. Finally, we changed the connective weights between the neurons to simulate individual differences. The simulation results lead us to believe that the inhibitory connections from piriform cortex to olfactory bulb may contribute to the individual differences that are observed in the behavioral experiment.

1 Introduction

In recent years, the demand for odor processing apparatuses has been increasing in fragrance and entertainment industries. Odorant information is one that is difficult to handle because it is composed of a combination of 200 to 400 thousands of molecules [2], thereby forming high-dimensional information. Therefore, it requires vast amounts of computation to discriminate or classify odors. Thus far, to reduce the dimension of odorant information, the ability of most odor discriminating apparatuses, for example, an electronic nose for banana ripeness developed by Llobet *et al.* [3] has been specialized for particular odors; further, it is not comparable to that of a living nose. Therefore, learning from the olfactory system of a living nose would be one of the most efficient and prospective approaches.

A number of studies have been reported on the olfactory system of mice. It can be considered to have



(a) There are 200 to 400 thousands kinds of odorant molcules. (b) Mice only pay attention on a part of molcules composing an odor.

Figure 1: The concept of attention behavior

three parts : olfactory receptors (ORs), which respond to odorant molecules; an olfactory bulb (OB), which performs the integrated process of the response of the ORs; and a piriform cortex (PC), which discriminates the odorants based on the information provided by the OB [2] (Fig.2). Haberly *et al.* [4] have revealed more detailed structure of the olfactory system anatomically. Through a series of behavioral experiments on odor discrimination, Nakamura *et al.* [1] reported that mice could identify an odor focussing on only a part of components composing the odors. It was also observed that each individual focuses on different components. This behavior is termed as "attention." The mechanism of attention was researched by Li *et al.* [5] using their computer model of the OB; they referred to attention as "adaptation". Li *et al.* suggested that an inhibitory signal to the OB might be one of the causes of attention. However, the origin of the inhibitory signal and its control mechanism is still unknown; thus, the mechanism of attention has not been completely elucidated.

In this research, we first construct a novel artificial neural network model of the olfactory system that consists of OR, OB, and PC based on biological insights [4]. In the proposed model, the inhibitory connection from the PC to the OB reported by Heimer [6] are also taken into account. Then, a series of computer

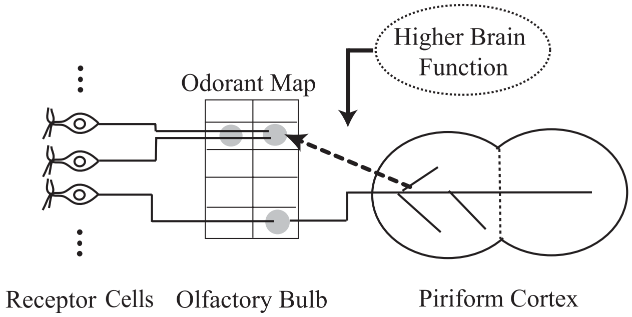


Figure 2: Schematic figure of the olfactory system.

simulations of the model is carried out with changes in the inhibitory connections. The simulation results are compared to the result of the behavioral experiment performed by Nakamura *et al.* to elucidate the mechanism of attention. In this paper, we report that the inhibitory connections from the PC to the OB can cause attention, and differences in the inhibitory connections can cause the individual differences among mice.

2 Behavioral experiments for odor discrimination of mice

Nakamura *et al.* implemented a series of behavioral experiments on odor discrimination by mice to reveal the behavior of attention. This section describes the experiments and its results.

2.1 Methods

The behavioral experiments on odor discrimination by mice were carried out by Nakamura *et al.* [1] using a Y-shaped passage (Y-maze), as shown in Fig.3. First, a mouse that is deprived of water is placed at the start point (point C). The mouse was allowed to drink water as a reward only if it chose the correct point-A or B-from where the odor emanated. Then, one trial was defined as the duration from the mice starting at point C to its arrival at either point A or B. Twenty-four trials, which were defined as one session, were performed in a day for each mouse. The accuracy rate at which the mice chose the rewarded odor was recorded. When the correct rate surpassed eighty percent, it was considered that the mice have learnt the rewarded odor. Because the experiments required discriminating between two kinds of odors, an accuracy rate of fifty percent indicates that the mice could not discriminate between the odors at all. In the experiments, the mice were to learn an rewarded odor [Ci:EB:IA] that composed of three types of molecules-isoamyl acetate (IA), ethyl butyl (EB), and citral (Ci). Then,

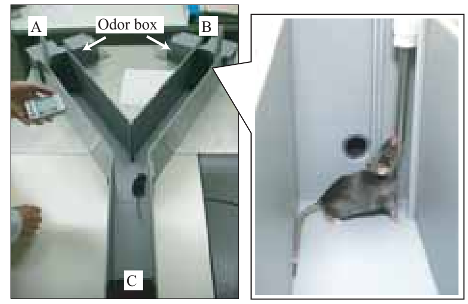


Figure 3: Structure of Y-maze and drinking behavior of mouse (revised from the figure in the literature 1.)

the mice were made to discriminate the rewarded odor from the odors containing the same types of molecules as the rewarded odor ([Ci], [EB], [IA], and [EB:IA]) [1].

2.2 Results

Fig.4 shows the experimental results of two out of the eight individuals on whom the experiment was performed. In Fig.4, the vertical and horizontal axes show the accuracy rate and the odors for discrimination, respectively.

In the case of individual A, we observe that the accuracy rates for odors containing the EB molecule ([EB], [EB:IA]) are approximately fifty percent. This result implies that individual A paid attention only on the EB molecules to discriminate between the odors; therefore, it could not discriminate between the odors of [EB] and [EB:IA] from the rewarded odor containing the EB molecules. Two out of eight individuals paid attention on the EB molecules.

Now, in the case of individual B, we observed that the accuracy rate for odor [EB:IA] is approximately fifty percent. This result implies that individual B paid attention to the combination of molecules EB and IA. It was observed that five out of eight individuals paid attention to the combination of EB and IA.

From these results, Nakamura *et al.* suggested that the mice pay attention to a part of the molecules that is contained in the odors to perform the odor discrimination task; further, there are individual differences between the mice with respect to the molecules that they would pay attention to.

3 A model of the olfactory system of mice

In this section, we propose a model of the olfactory system constructed based on biological insights. An overview of the proposed model is shown in Fig.5. In

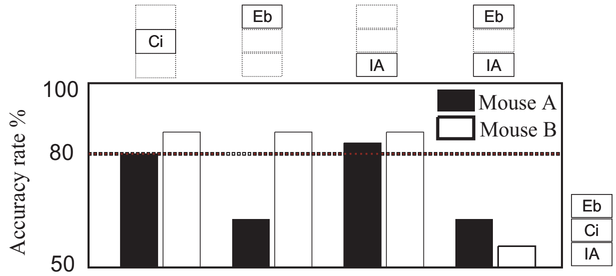


Figure 4: Results of odor discrimination experiment.(unpublished data)

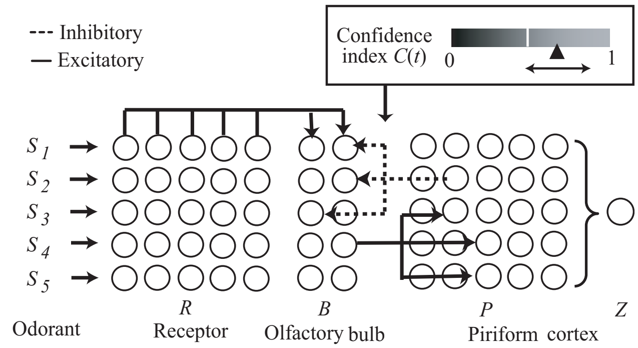


Figure 5: A model of the olfactory system in mouse.

Fig.5, the R layer comprises olfactory receptors (ORs) that respond to odorant molecules; B layer, the olfactory bulb (OB); P layer, the anterior piriform cortex; and Z layer, the post piriform cortex that outputs the discrimination results. Each layer consists of a neuron model, and the neuron models are connected based on the biological insights [4], [6]. The connective weights are subject to change by Hebbian learning rule. The details of each layer are given below.

3.1 Receptor layer

There are about 1000 types of ORs in the nasal passage of mice, and each type of OR responds to different types of molecules [7]. The proposed model is designed to discriminate odors that consist of N types of molecules $S_1, S_2, \cdots S_N$; thus, the R layer is composed of N types of receptors. The density of each molecule is expressed as a value in the interval [0, 1]. The receptor model is defined by using the following equation according to the general neuron model, which is expressed as the sigmoid function [8]:

$$U_{R(i,j)}(t) \quad = \quad \frac{1}{1+\exp\{-\epsilon_{R(i,j)}(u_{R(i,j)}(t)-\theta_{R(i,j)})\}}, \tag{1}$$

where ϵ is the gradient of sigmoid function; $u(t)$, the internal state of a neuron at time step t; and θ, the firing threshold of the neuron. Each receptor of the j column in the R layer, which is shown in Fig.5, responds to the same molecule S_j with a different firing threshold θ. The internal state of each receptor in the R layer is defined as $u_{l(i,j)}(t) = s_i(t)$. The output of the receptors calculated by equation (1) are inputted to the OB layer (B layer).

3.2 Olfactory bulb layer

The olfactory bulb consists of glomeruli, excitatory neurons known as mitral cells, and inhibitory neurons known as granule cells. Glomeruli are a convergence of the nerve terminal extending from the olfactory receptors, and they map the responded molecules. There are around 1000 pairs of glomeruli on the olfactory bulb surface. The response pattern of the glomeruli is called odorant map [9]. The outputs of the glomeruli are transmitted to the mitral cells. Further, the mitral cells receive an inhibitory input from the PC via the granule cells [6].

In the proposed model, the gromeruli is omitted for simplification, and the receptor $R_{i,j}$ that responds to the same molecule S_j is directly connected to the same mitral cell $B_{i,j}$. Mitral cell $B_{i,j}$ maps molecule S_j, and the firing pattern of the B layer represents the odorant map-mediated mitral cells. The neurons in the B layer receive excitatory input from the R layer and inhibitory input from the P layer; thus, the internal states $u_{B(i,j)}(t)$ are as follows:

$$\begin{aligned} u(t)_{B(i,j)} = & \sum_{R(m,n)} w(t)_{R(m,n),B(i,j)}\ U_{R(m,n)(t)} \\ & - \sum_{P(x,y)} w_{P(x,y),B(i,j)}(t)\ U(t)_{P(x,y)}, \end{aligned} \tag{2}$$

where $w_{R(m,n),B(i,j)}, w_{P(m,n),B(i,j)}$ are the connective weights from the B and P layers, respectively. The output of each neuron, $U_{B(i,j)}(t)$, is expressed as a sigmoid function in equation (1). The outputs of mitral cells are transmitted to neurons in the PC.

3.3 Piriform cortex layer

The PC can be divided into anterior piriform cortex (APC) and posterior piriform cortex (PPC). It is considered that the APC processes the input from the OB, while the PPC discriminates the odor [4]. Therefore, in the proposed model, the PC layer was divided into the P and Z layers. Further, it was found by Heimer *et al.* that inhibitory connections exist from the PC to the OB [6]. However, these connections are very complex and consist of individual difference, and hence, the connections between the B and P layers are randomly connected in the proposed model. The internal state $u_{P(i,j)}(t)$ of each neuron in the P layer is given by the following equation:

$$u_{P(i,j)}(t) = \sum_{B(m,n)} w_{B(m,n),P(i,j)}(t)\, U_{B(m,n)}(t), \quad (3)$$

where $w_{B(m,n),P(i,j)}(t)$ are the connective weights from the B layer to the P layer. On the other hand, the internal state $u_Z(t)$ of the neuron in the Z layer is given by the following equation:

$$u_Z(t) = \sum_{P(m,n)} w_{P(m,n),Z}(t)\, U_{P(m,n)}(t), \quad (4)$$

where $w_{P(m,n),Z}(t)$ are the connective weights from the P layer to the Z layer. Similar to the R and B layers, the output of each neuron in the P and Z layers is defined as a sigmoid function of equation (1).

The discrimination result was obtained according to the output of the Z layer. Output $U_Z < 0.5$ indicates that the model has discriminated the odor as unrewarded odor, while output $U_Z \geq 0.5$ indicates rewarded odor. In this way, the Z layer discriminates odor based on the output of the P layer.

3.4 Learning algorithm

The connective weights between the neurons in each layer are initialized by a uniform random value of interval [0, 1] and are updated by the Hebbian learning rule [10]:

$$w_{l(m,n),k(i,j)}(t+1) = w_{l(m,n),k(i,j)}(t) + \delta w(t)_{l(m,n),k(i,j)},$$
$$\delta w_{l(m,n),k(i,j)}(t) = \alpha\{U(t)_{k(i,j)} - b_k\}\{U(t)_{l(m,n)} - b_l\},$$

where α is the learning rate; b_l and b_k are the thresholds of the change in the sign of $\delta w_{l(m,n),k(i,j)}(t)$. The connective weights between the B, P and P, Z layers are updated by the Hebbian rule. The connection between the R, B layer are considered to be genetically determined [9] and as a result the connective weights remained unchanged.

Learning is assumed to be controlled by a higher brain function. For simplification, the higher brain function is modeled as confidence index $C(t)$ $(0 \leq C(t) \leq 1)$. When the discrimination result is correct, the confidence index increases by $1/n$, while for an incorrect result, the confidence index decreases by $1/n$. Here, n is defined as a constant number representing the volatility of the confidence index. When

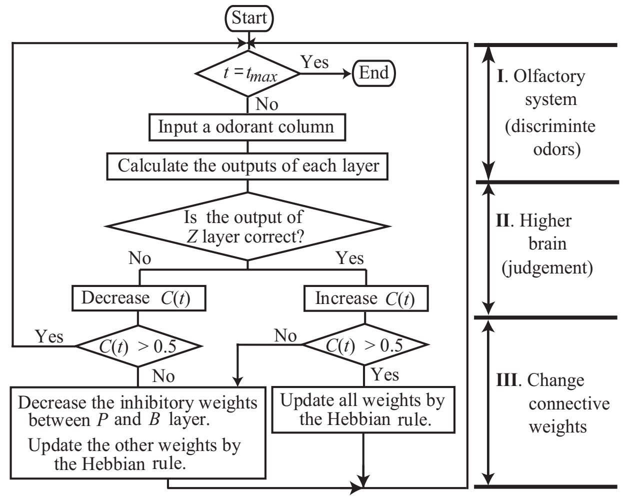


Figure 6: The flowchart of weight training.

the confidence index $C(t) \geq \theta_c$, the inhibitory connection, from the P layer to the B layer, is updated by the Hebbian learning rule, while when $C(t) < \theta_c$, the inhibitory connection is decreased by a constant rate β $(0 \leq \beta \leq 1)$. The learning algorithm can be summarized in Fig.6.

4 Simulation

In this section, a series of simulations is performed to confirm if the proposed model can simulate attention behavior and individual differences.

4.1 Simulation of learning and attention

First, the connection between the B and P layers was initialized to a random value in the interval $[0, 1]$. For this initial state, the model was labeled as a neural network model M1. One step was defined as from inputting molecules to R layer to output of Z layer. The rewarded odor A $(N = 5, s_1 = s_2 = s_3 = 1, s_4 = s_5 = 0)$was repeatedly inputted to the model for 15 steps. While these steps were carried out, the weights were subject to be updated toward the neuron in Z layer fires stronger by the algorithm shown in Fig.6.

The changes in the outputs of the neural network model M1 is shown in Fig.7; where (a) and (b) show the firing patterns of each layer when $t = 1$ and $t = 15$, respectively. The output of each neuron is represented by a square. The larger the output of the neuron is, the whiter the corresponding square is. The changes in the inhibitory weights from the P layer to the B layer and the confidence indices are also shown in Fig.9 and Fig.10, respectively. From Fig.7(a), it can be observed that the neuron in the Z layer fires weakly when

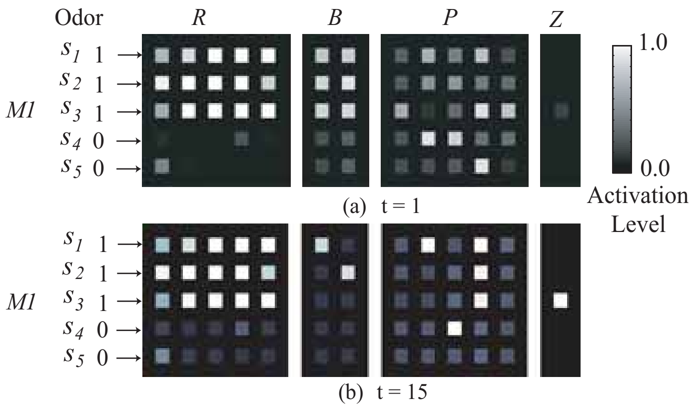


Figure 7: Changes in output states of M1.

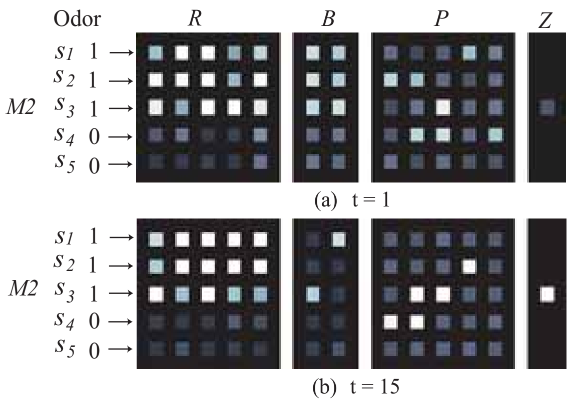


Figure 8: Changes in output states of M2.

$t = 1$. This means that the model discriminated the odor as unrewarded odor, which is incorrect discrimination. After the rewarded odor A was repeatedly inputted, connective weights were updated by the algorithm shown in Fig.6; thus, the model M1 learnt odor A as the rewarded odor. This result can be observed in Fig.7(b) in which the neuron in the Z layer fires strongly when $t = 15$.

At the same time, the inhibitory connective weights from the P layer to the B layer increases, for example, the inhibitory weights from $P_{4,3}$ to $B_{3,2}$ increase, as shown in Fig.9. Hence, the neurons mapping molecule S_3 were inhibited. As the result, the model M1 discriminates odors only by molecules S_1 and S_2, for which the attention ability of the model M1 has been confirmed.

Next, the same simulation, which was described above, was carried out for another neural network model M2, which is initialized with different connective weights of inhibitory connections from the P layer to the B layer. This simulation result is shown in Fig.11; (a) and (b) show the firing pattern when $t = 1$ and $t = 15$, respectively. When $t = 15$, the model learnt odor A as a rewarded odor because the neuron

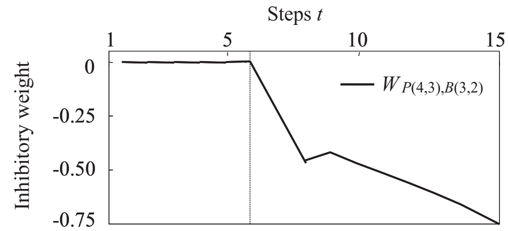


Figure 9: Changes in inhibitory weight from the P to the B layers.

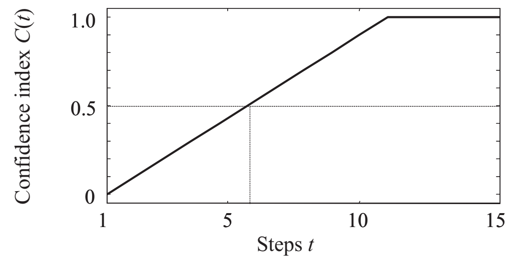


Figure 10: Changes in the confidence index.

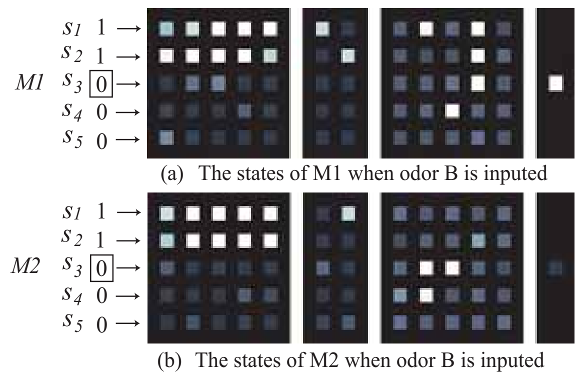


Figure 11: The states of M1 and M2 when odor B is inputed.

in the Z layer fired strongly. It can be also observed that M2 has paid attention to molecules S_1 and S_3, while M1 has paid attention on S_1 and S_2. These results suggest that the difference in the initial weights of inhibitory connections from the P layer to the Blayer can make the proposed model pay attention to different molecules.

4.2 Individual differences in attention

In section 4.1, the neural network models M1 and M2 have learnt to discriminate the rewarded odor A by paying attention to the different molecules. Here, to determine the discrimination ability of both the models, an unrewarded odor B, which contained some of the common molecules from the rewarded odor A, is inputted to M1 and M2.

The result is shown in Fig.11. Fig.11(a) and (b) show the outputs of M1 and M2 respectively when the unrewarded odor B is inputted. It can be observed from Fig.11(b) that the neuron in Z layer fired weakly, thus M2 has successfully discriminated the odor B as the unrewarded one. However, M1 has discriminated it as the rewarded odor A, because the neuron in Z layer fired strongly as the same way when the odor A was inputted. In the simulation described in the previous section, M1 has paid attention to molecules S_1 and S_2. Therefore, whenever the inputed odor contains both molcules S_1 and S_2, M1 would discriminate it as the rewareded odor A.

These simulation results correspond to the behavioral experiment carried out by Nakamura *et al.* [1], which was described in section 2. Further, the results lead us to believe that the individual differences in odor discrimination could be caused by differences in inhibitory connections from the anterior piriform cortex (P layer) to the olfactory bulb (B layer). As mentioned in section 1, Li *et al.* [5] have suggested that the attention is caused by inhibitory signal. Our simulation results support their hypothesis and imply that the unspecified origin of the inhibitory connection might be the anterior piriform cortex.

5 Conclusion

In this paper, we focused on the attention behavior of mice observed from behavioral experiments, and proposed a neural network model of their olfactory system based on biological insights. A series of simulations of the proposed model was carried out so that the attention behavior was observed. Also, by changing the inhibitory connection from piriform cortex to olfactory bulb, a possible cause of the individual differences in attention was discussed.

Although the proposed model is a macroscopic model, the simulation results showed that it captured the feature observed in the odorant discrimination experiment of mice. Further works have to be carried out to enable the model to deal with more complicated odorant information like odors that exist in the real world. Therefore, for next step, we are planning to improve the receptor model and olfactory bulb model.

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