Odor Discrimination Using Neural Decoding of Olfactory Bulbs in Rats

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Abstract—This paper presents a novel method for inferring the odor based on neural activities observed from rats' main olfactory bulbs. Multi-channel extra-cellular single unit recordings were done by micro-wire electrodes (tungsten, 50μm, 32 channels) implanted in the mitral/tufted cell layers of the main olfactory bulb of anesthetized rats to obtain neural responses to various odors. Neural response as a key feature was measured by substraction of neural firing rate before stimulus from after. For odor inference, we have developed a decoding method based on the maximum likelihood (ML) estimation. The results have shown that the average decoding accuracy is about 100.0%, 96.0%, 84.0%, and 100.0% with four rats, respectively. This work has profound implications for a novel brain-machine interface system for odor inference.

Keywords—biomedical signal processing, neural engineering, olfactory,neural decoding, BMI

I. INTRODUCTION

NEURONS represent and transmit information by firing sequences of spikes in various temporal patterns [1]. These neural spike patterns contain responses to external stimulus if these neurons are sensory neurons that are activated by external sensory input. Thus the external sensory input can be inferred from neural spike patterns. This is so called *neural decoding*.

Many neural decoding algorithms have been developed. The simplest approach uses a linear estimator [2], which has been used effectively for real-time neural control of a 2D cursor in brain-computer interface research [3]. But this approach requires the use of data over a long time window [4]. One of the popular approach for neural decoding is to use artificial neural networks [5][6]. In addition Kalman filter based methods have been exploited for inferring hand position and velocity [4][7]. These neural decoding algorithms have been focused on predicting arm motion, intended reach, and cursor control [8]–[9]. In [10], finger movements have been inferred from M1 neurons using the maximum likelihood (ML) method. However, neural decoding of olfactory system has not been studied widely.

Mammals' olfactory systems are capable of distinguishing thousands of odorous compounds. Different odorants induce odor-specific spatial patterns of olfactory bulb glomerular layer activity [11]. The olfactory bulb glomeruli receive inputs from a homogeneous population of olfactory receptor neurons expressing the same olfactory receptor gene [12]. Glomeruli serve as the site of synaptic contact between olfactory receptor neurons and second-order neurons, mitral/tufted cells. Most naturally occurring odors are complex mixtures, and the spatial pattern of glomerular activity reflects both individual components [13] and early inter-component interactions [14]. In addition to spatial patterns, both glomerular and mitral/tufted cell activities demonstrate stimulus-specific temporal structure [15].

Here, we present a statistically optimal method, based on the ML method, for decoding the activity of a large number of simultaneously recorded MOB neurons during presentation of various odors. The ML method is an optimal statistical method to make inference about parameters based on the underlying probability distribution of a given data set. Also, in [9] the authors have provided a neuron model that can realize the likelihood function for an optimal decoding of sensory information. One of the challenging tasks in ML decoding is to model the probability density function of the activity change of a neuron. For modelling of neuronal discharge patterns, we quantified the activity of each neuron as the change in firing rate before and after odor stimulus. The mathematical modelling is done by using the Gaussian distribution. Then we inferred the odor for which the Gaussian based likelihood function has a maximum.

II. MATERIALS AND METHODS

A. Odor presentation

All experimental procedures were in accord with the guidelines for animal experimentation in Hallym University. Male Sprague-Dawley rats (350–400g, 4 rats) were used as subjects. Animals had food and water available ad libitum and were housed on a 12h light/dark cycle.

Odor delivery was performed during the light phase of the cycle. Odorants were delivered with a motorized odor stimulator, presented 10mm from the rat's nose for 4.0 seconds with clean air. Approximate concentration was assumed at 1:1 airflow dilution in clean air. Each stimulus was at an interval of about 120.0 seconds and repeated five times for each experiment. Five organic compound were used as test odorants. Isoamyl acetate (IAA), Methyl methacrylate (MMA), Methyl ethyl ketone (MEK), Mixture (MIX), and Mineral oil (OIL).

B. Signal acquisition from MOB neurons

Micro-wire electrodes (32 channels, bare diameter 50μm/coated diameter 100μm-Teflon insulated tungsten wire) were implanted in the dorsal area of MOB of anesthetized rats (urethane 1.5g/kg, i.p., Sigma (Cat. U2500)). Neural activities

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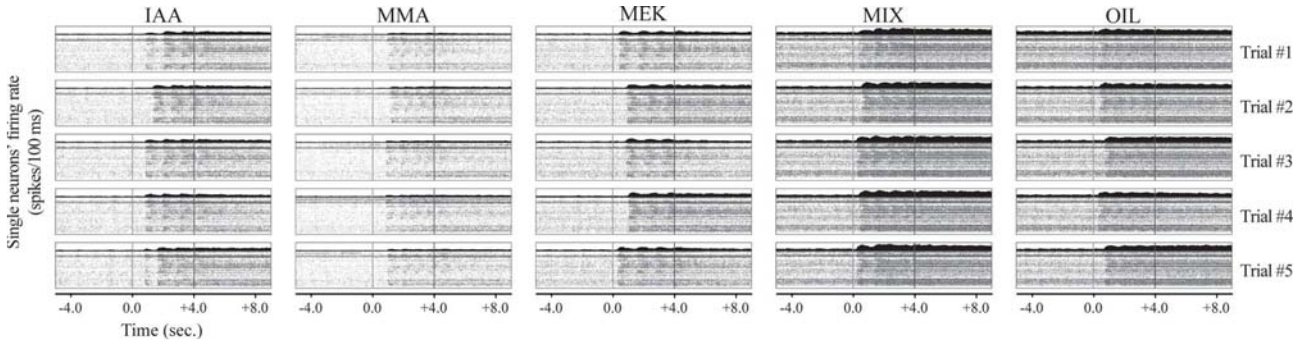International Journal of Bioengineering and Life Sciences
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Fig. 1. Peristimulus time histograms (PSTHs, top of each graph) and rasters (bottom of each graph) of total 128 neurons over five trials on rat A. PSTHs visualize the neural firing rate (spike counts/100 ms) in relation to presentation of 5 different odor stimuli. Odor stimuli for 4.0 seconds are marked with two vertical lines.

were assessed by simultaneously recording extra-cellular single-unit activities from many mitral/tufted cells.

Signals from individual electrodes were amplified by $10,000 - 20,000$ gain, filtered from 154Hz to 8.8kHz. A Many Neuron Acquisition Processor (MNAP; Plexon Inc., Dallas, TX) was used to simultaneously record neural activities from multiple microwires. Data were recorded from 128 odor-responsive neurons in MOB of the rats.

C. Data analysis

Let $r_n(k)$ be the average neural activity of a neuron during an odor stimulus, i.e., firing rate of neuron #n for an odor stimulus k among five possible choices. We defined odor-evoked neural response by

$$x_n(k) = r_n(k) - r_n(k_0) \qquad (1)$$

where $r_n(k_0)$ is the initial activity of neuron which means average firing rate before the odor k delivery. The magnitude of the odor-evoked response $x_n(k)$ was calculated by subtracting the number of spikes that occurred before the stimulus (initial) onset from the number of spikes that occurred (during 4.0 sec.) after the stimulus onset.

1) Neural decoding using maximum likelihood method: We used the ML estimation method for each odor stimulus. The ML method estimates an unknown parameter, k, so that the probability density function $p(x_1(k), x_2(k), \ldots, x_N(k))$ as likelihood function is maximized, i.e.,

$$\hat{k} = \arg\max_k p(x_1(k), x_2(k), \ldots, x_N(k)) \qquad (2)$$

where N is the total number of neurons used for the ML decoding. Although the neurons' activities may be not statistically independent in the physiological view, to avoid mathematical complication we assumed that the $x_i(k)$ and $x_j(k)$ are independent as in [10] and [9]. Thus, the following is satisfied

$$p(x_1(k), x_2(k), \ldots, x_N(k)) = \prod_{n=1}^{N} p(x_n(k)) \qquad (3)$$

and finally based on (2) the odor stimuli is estimated by

$$\hat{k} = \arg\max_k \prod_{n=1}^{N} p(x_n(k)). \qquad (4)$$

2) Modelling the probability density of neural response: The probability density function was modelled by using the Gaussian distribution. The Gaussian probability density function for each neuron's response is given by

$$p(x_n(k)) = \frac{1}{\sqrt{2\pi\sigma_n^2(k)}}\exp[-\frac{(x_n(k) - \mu_n(k))^2}{2\sigma_n^2(k)}] \qquad (5)$$

where $\mu_n(k)$ is the ensemble mean of $x_n(k)$, i.e., $\mu_n(k) = E[x_n(k)]$. Also $\sigma_n^2(k)$ is the variance of $(x_n(k)$, i.e., $\sigma_n^2(k) = E[(x_n(k) - \mu_n(k))^2]$. Thus to estimate an unknown odor stimulus, all that we need are $\mu_n(k)$ and $\sigma_n^2(k)$, which can also be estimated from training data sets.

III. RESULTS

We have examined the performance of the proposed method. The number of spikes was calculated in 100 ms bins, and the firing rate $r_n(k)$ was obtained by averaging the number of spikes in 40 bins for 4.0 seconds during odor stimuli. The initial activity, $r_n(k_0)$ was obtained by averaging in 100 bins for 10.0 seconds before odor stimuli. Figure 1 shows peristimulus time histograms (top of each graph) of neural firing rate of total single neurons during five odor stimuli and examples (bottom of each graph) of rasters (neural spike trains) of total 128 neurons. Rasters indicate sparse and dense spikes occurrences. Beginning and ending points of odor stimulus for 4.0 seconds are marked with two vertical lines.

Figure 2 represents probabilistic models of odor-evoked neural responses. The probability density functions of neural response of broadly tuned neuron #53 shown in Fig. 2(a) indicate that they are clearly distinguishable across all odorants because they, $x_{53}(k)$ are significantly different across odorants, k. The probability density functions of neural response of highly tuned neuron #6 shown in Fig. 2(b) indicate that 'MIX' can be clearly distinguished from other four odorants but 'MEK' and 'IAA' cannot be differentiated from each other because they show small activity change. The probability density functions of neural response of broadly tuned neuron #18 shown in Fig. 2(c) indicate that odorants cannot be distinguished more clearly than neuron #53 because the models overlap much. The probability density functions of neural response of neuron #14 shown in Fig. 2(d) indicate

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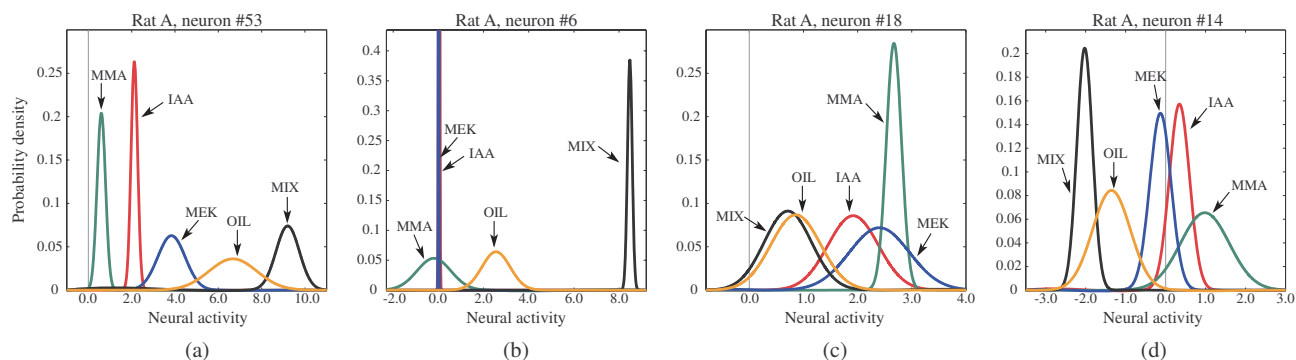Vol:5, No:11, 2011

Fig. 2. Probability density models of odor-evoked neural responses on rat A. (a) neuron #53 (b) neuron #6 (c) neuron #18 (d) neuron #14.
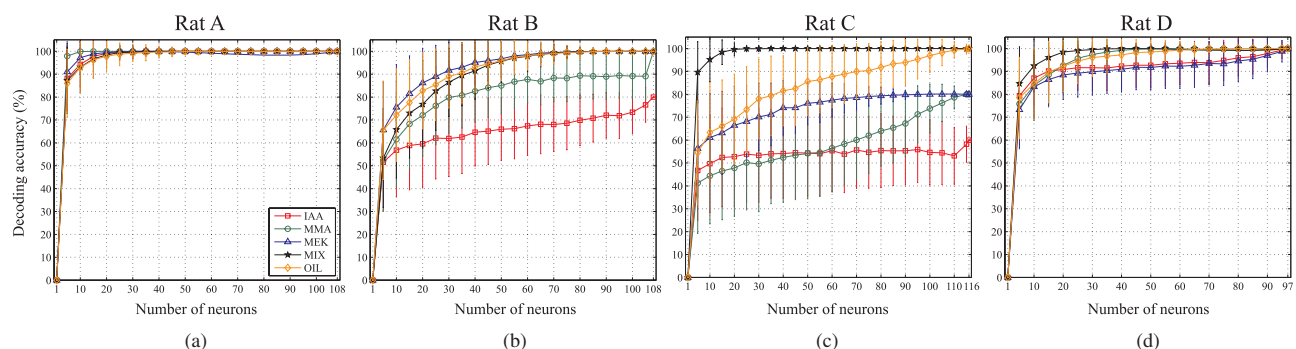

Fig. 3. Decoding results for five odor stimuli. Each subplot depicts accuracies for four rats. Maximum average decoding accuracy was 100% for rat A, 96.00% for rat B, 84.00% for rat C, and 100% for rat D. (a) rat A (b) rat B (c) rat C (d) rat D.

that odorants can be distinguished even though they suppressed neural responses.

Figure 3 shows the average decoding accuracy across the five odor stimuli for rat A, rat B, rat C and rat D. From the five trials, four trials were used to estimate variables such as $\mu_n(k)$, $\mu_n(k_0)$, and $\sigma_n(k)$. This estimation is simply done by averaging the independent four trials, e.g., $\mu_n(k) = \frac{1}{4}\sum_{m=1}^{4} x_n(k|$ in m^{th} trial). The remaining one trial was set aside for test data. In this case, we have five different combinations for choosing the test data. The performance of the ML decoding was evaluated by randomly choosing N neurons and this random selection was repeated $1,000$ times. Thus, the success rate in Fig. 3 are averaged over $5 \times 1,000 \times 5 = 25,000$ for each N.

The number of total recorded neurons is 128 but we excluded neurons which did not contain any spike firings during the overall experiment. Thus, for rat A, B, C, and D the numbers of valid neurons were 108, 108, 116, and 97, respectively. Using 100 neurons, the average decoding accuracy was as high as 100.00% for rat A, 92.53% for rat B, 81.07% for rat C, and 100.0% for rat D (Only 97 neurons were used for rat D). Using 50 neurons, the average decoding accuracy was as high as 99.99% for rat A, 87.83% for rat B, 74.06% for rat C, and 96.55% for rat D. Using only 10 neurons, the average decoding accuracy was as high as 95.48% for rat A, 66.58% for rat B, 65.31% for rat C, and 90.18% for rat D.

IV. CONCLUSIONS

We have carried out simultaneous many single neuron recordings from MOB of anesthetized rats during presentation of various odors. Most of MOB neurons have exhibited different increases of firing rate during various odor presentations. In most neural decoding researches, neural firing rate was modelled using absolute firing rate. Since the proposed Gaussian based odor-evoked neural response model considers neural activities both before and after odor stimulus, it could quantify olfactory neural responses better than the models using the absolute firing rate. Also, the proposed ML-based decoding method is computationally efficient. We hope that our results will trigger a novel brain-machine interface for discrimination of various odors. This concept of BMI system could be used for detecting drugs or dangerous objects.

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