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Odor Sensing System with Multi-dimensional Data Analysis

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Abstract

There are two recent topics in odor sensing system. One is an odor biosensor using actual olfactory receptors. The other is deep leaning technique to predict odor impressions. The author believes these are key technologies to realize a sophisticated olfactory sensor.

1. Introduction

In our olfactory system, an output pattern of various types of olfactory receptor neurons with partially overlapping specificities is recognized by an olfactory neuron system [1]. Thus, biomimetic approach to realize an artificial sensing system using an array of sensors followed by pattern recognition was proposed [2-3]. Although this type of odor sensing system is called an electronic nose, its sensitivity, selectivity and stability should be further improved. Here, we introduce a biomimetic odor sensing system using the cells expressing plural types of olfactory receptors [4].

Then, deep learning technique to predict odor impression was studied [5]. The mass spectrum data were mapped onto result of sensory test using large-scale neural network. Moreover, a neural network to predict wide-range of data was studied since small peaks in mass spectrum has much contribution to prediction [6]. The recent results related to odor sensing system are explained in this presentation.

2. Odor biosensor

Principle of odor recognition in the living body is shown in Fig.1. Although each OR (Olfactory Receptor) responds to multiple odorants, its output pattern from an array of ORs is unique. Thus, odorants are recognized using pattern recognition technique. Although this technique is also used for artificial sensing system, the selectivity is still not enough even if the combination of the sensor array with pattern recognition is used. Thus, we study odor biosensors.

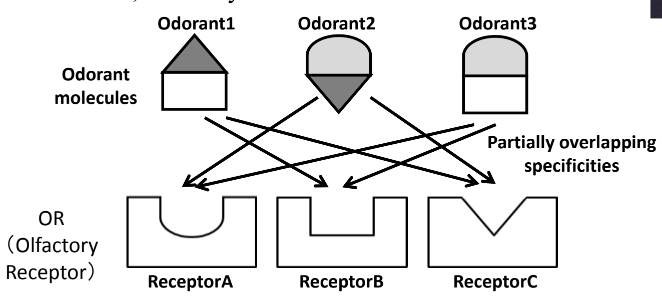
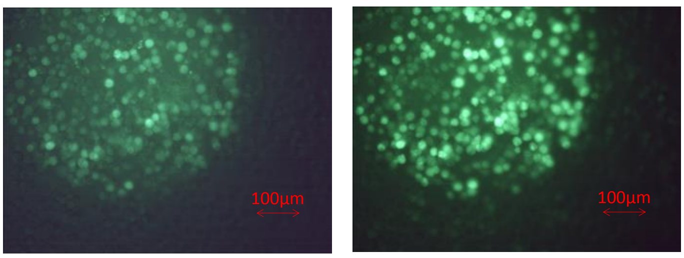


Fig.1 Principle of odor recognition.

We use insect ORs because of their simple structures and mechanism. Sf21 cells expressing Drosophila ORs were used here. Since Fluorescent protein inside the cell is sensitive to calcium ion, the increase in calcium ion concentration inside the cell caused by ion channel opening due to odorant reception changes the intensity of fluorescent light [7]. Figs.2 (a) and (b) show the fluorescent image of Sf21 cell expressing OR56a before and after geosmin injection. Geosmin has a typical moldy smell. The fluorescent intensity increased after geosmin injection as OR56a captures geosmin. Thus, the intensity change of fluorescent light is used as a sensor output. Fluorescent image of the cells was taken by CMOS camera though a dichroic mirror. Lock-in technique was used to detect the fluorescent light synchronous with the modulated light from a laser diode.

After the experiment on single OR, the cells with two types of ORs were randomly distributed in a chamber. Although the cell patterning technique was not required in our method, the image recognition technique was used to classify odors. When the cells were exposed to the odor several times, the sensor response gradually decreased probably due to photo breaching. However, two types of moldy smells such as geosmin and 1-octen-3-ol were correctly classified in spite of large fluctuations of the sensor responses just using linear discrimination analysis. The high classification rate was achieved because of excellent sensor selectivities originating from OR characteristics.



(a) (b)

Fig. 2 Fluorescent images of Sf21 cell expressing OR56a before geosmin injection (a) and after its injection (b).

3. Deep learning technique to predict odor impression

The odor impression obtained from sensory test was predicted using mass-spectrum data and deep learning technique [4]. The mass spectrum is used here since its large-scale database is available and it has large dimensional data including plenty of information.

The sensory test data based upon SD (Semantic Differential) method, conducted by Dravnieks were used here [8]. In that database, 144 descriptors including adjectives such as warm, sweaty, fruity etc. have scores from 0 to 5 for 121 odorants.

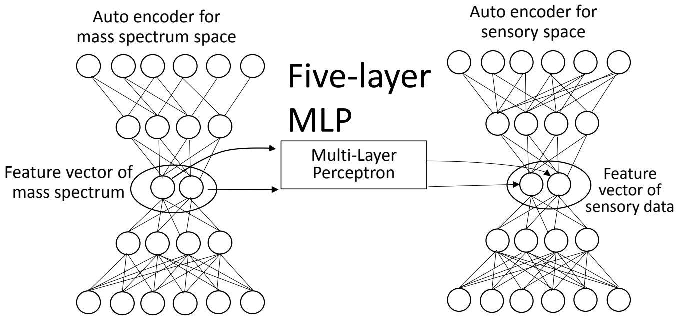


Fig.3 Schematic diagram of odor-impression prediction.

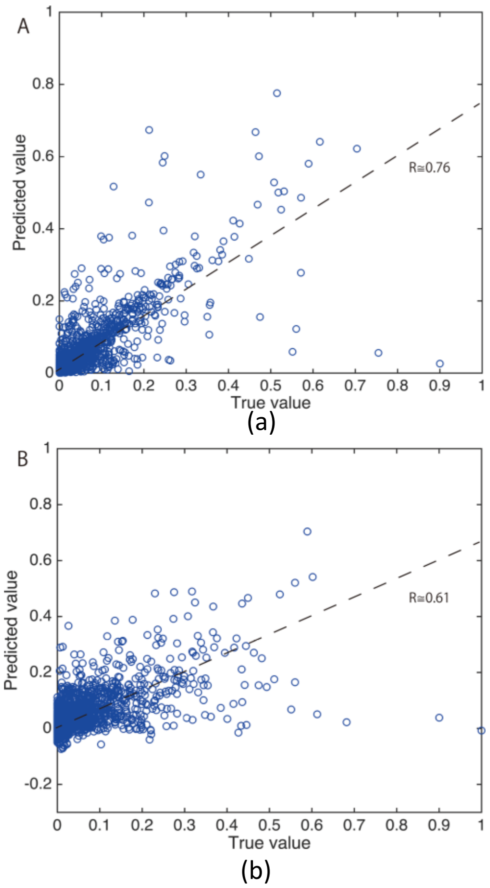


Fig.4 Result of odor impression prediction. (a) proposed method and (b) PLS method [5]. Score is normalized between 0 and 1.

The schematic diagram of odor-impression prediction is illustrated in Fig.3. Deep-learning neural network used here includes two five-layer auto encoders, one for input data space (mass spectrum) and the other for output space (sensory data) to extract the features. Then, the feature vector of the mass spectrum was mapped onto the feature vector of sensory data using five-layer perceptron (MLP). The sensory data were reconstructed using the auto encoder at output space. The dimensions of feature vectors for mass spectrum and sensory data were 45 and 30, respectively after the optimization. In the prediction after training, totally nine-layer neural network was used.

The result of odor-impression prediction is shown in Fig.4 (a) together with the result obtained using PLS (Partial Least Squares), typical regression method used in chemometrics as is shown in Fig.4 (b). The number of latent variables in PLS was 45 after the optimization. The cross validation technique was used for the evaluation in both cases. The true value in the figures comes from the database [8]. The plots approach the diagonal line if the accuracy is high. It was found that the correlation coefficient of the proposed method (≅ 0.76) was higher than that of the conventional method such as PLS (≅ 0.61). Further improvement is expected if more data are available.

3. Conclusions

Odor biosensor and deep learning for odor-impression prediction were separately explained here. Both works can be combined in the future. Other work such as odor recorder and olfactory display described elsewhere [9] can be introduce at the next opportunity.

Acknowledgements

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