Abstract—We characterize the hemodynamic response changes in the main olfactory bulb (MOB) of anesthetized rats with near-infrared spectroscopy (NIRS) during the presentation of three different odorants: (i) plain air as a reference (Blank), (ii) 2-heptanone (HEP), and (iii) isopropylbenzene (Ib). Odorants generate different changes in the concentrations of oxy-hemoglobin. Our results suggest that NIRS technology might be useful in discriminating various odorants in a non-invasive manner using animals with a superb olfactory system.

Keywords—brain-machine interface (BMI), functional near-infrared spectroscopy (fNIRS), main olfactory bulb (MOB), Oxy-hemoglobin (HbO₂), Beer–Lambert law, maximum likelihood estimation (MLE).

I. INTRODUCTION

NEAR infrared spectroscopy (NRIS) is a technique that enables the noninvasive measurement of concentration changes and optical coefficients (scattering and absorption coefficients) in chromophores, such as Oxy-hemoglobin (HbO₂), Deoxy-hemoglobin (Hbr), myoglobin, cytochrome oxidase, water, lipid, and protein, in human tissues using lights that are harmless to the human body. Since Jobsis first measured tissue oxygenation in human tissues [1], NRIS has been used extensively not only in the analysis of the metabolic process in human tissues, including neuroimaging, which visualizes brain activation; the diagnosis of breast cancer; neuroscience using small animals; and brain-machine interfaces (BMI), but also in the analysis of crop quality. In particular, near infrared rays in wavelengths of 600–900 nm have fewer occurrences of scattering and absorption in human tissues compared with other wavelengths. Thus, information inside the human body can be obtained using these rays.

Concentration changes in HbO₂ and Hbr are due to hemodynamic responses in blood vessels. An increased amount of HbO₂ flows in the surrounding tissues when the human metabolism becomes active. This study attempted to measure hemodynamic response changes in the main olfactory bulb (MOB) of rats when they are stimulated with odorants, using Imagent equipment in the frequency domain type. In order to measure hemodynamic changes, wavelengths around 800 nm, where the absorbencies of HbO₂ and Hbr become equal, were selected. In addition, 690 nm and 830 nm laser diodes were used in the Imagent system and optical coefficients were derived from the changes in the signal intensities of phase and light. Using the optical coefficients derived, odorants were reversely inferred from the hemodynamic changes in the MOB of rats when they were stimulated by odorants. This study performed an analysis on how concentration changes in the MOB of rats, according to odor stimulations, and their variations, according to the lapse of time, influence the reverse inference of odorants. When analyzing the concentration changes in the MOB of rats, this study used only the information of HbO₂.
II. MATERIALS AND METHODS

A. Experiment protocols

The experiment was performed in the Medicine and Physiology Laboratory, Hallym University, using Sprague Dawley (SD) rats (350–400 g, male), which were provided by the animal center of Orient Bio Co. The laboratory was maintained at 23±2°C and 55±10% humidity. Rats could freely take food and water in their cages. Rats were anesthetized by intraperitoneal injection using urethane (20%, 1.25 g/kg body weight). After fixing the rats on a stereotaxic device, their scalps were incised. Signals were then obtained after arranging optical fibers according to the location of coordinates.

Using the 16 source-channel frequency-domain NIRS system (Imagent, ISS, IL, USA), hemodynamic responses in the olfactory bulb were measured. This system uses two wavelengths, 690 nm and 830 nm, and each channel includes two 400 µm core diameter optical fibers (FT-400EMT, Thorlabs, NJ, USA) of 690 nm and 830 nm wavelengths.

Optical fibers were arranged as shown in Figure 2A and the actual experiment is shown in Figure 2B. In NIRS channels, sources and detectors were separated by 7 mm and the penetration of near infrared rays into the cortex area was 2 mm deep. Once optical fibers were arranged in the due location of coordinates, they were fixed to the rats’ skulls using dental cement (KetacCem, 3M, USA). Sampling was performed at 28.4 Hz in the NIRS system.

The rats were stimulated with diluted odors by connecting each bottle containing a chemical and a silicone tube. The chemicals used in the experimented were (i) natural air (Blank), (ii) 2-heptanone (Hep), and (iii) Isopropylbenzene (Ib).

B. Theory

In order to measure hemodynamic changes in the MOB of rats, the concentration changes in HbO2 and Hbr were calculated using the Beer–Lambert law. Transitivity (T) was derived by the following equation.

\[
T^{\lambda} = \frac{I^\lambda}{I_0^\lambda} = 10^{-LB^\lambda \sum_{m=1}^{M} \epsilon_m^\lambda c_m}
\]

(1)

\[I^\lambda\] is intensity of the received light corresponds to wavelength \(\lambda\), \(I_0^\lambda\) is intensity of the transmitted light corresponds to wavelength \(\lambda\).

\(\epsilon_m^\lambda\) is molar absorptivity of absorber at wavelength \(\lambda\) for molecular type \(m\), and \(C_m\) is concentration of molecular type \(m\). Absorbance (optical density) \(A\) is

\[
A^\lambda = \log_{10} \frac{1}{T^\lambda} = LB^\lambda \sum_{m=1}^{M} \epsilon_m^\lambda C_m = \log_{10} \frac{I_0^\lambda}{I^\lambda}
\]

(2)

\(L\) is pathlength, the distance between the source and detector, \(B^\lambda\) is differential pathlength factor \([4]\) (dimension less constant to account for photon path lengthening effect of scattering) corresponds to wavelength \(\lambda\).

In general matrix-vector equation is,

\[
A = LBE + C
\]

(3)

What we interested on is concentration vector \(C\).

\[
C = \frac{1}{L} (BE)^{-1} A
\]

(4)

In this experiments, \(S=2\) (830nm, 690nm) and \(M=2\) (Oxy-Hemoglobin, Deoxy-Hemoglobin).

\[
C_{diff} = \frac{1}{L} \left[ \begin{array}{c} B^{long} \epsilon_{O2Dib}^{long} \epsilon_{HbDib}^{long} \\ 0 B^{short} \epsilon_{O2Dib}^{short} \epsilon_{HbDib}^{short} \end{array} \right]^{-1} \left[ \begin{array}{c} \log_{10} I_{longDib} \\ \log_{10} I_{shortDib} \end{array} \right]
\]

(6)

During the progress of such an experiment, intensity values occasionally exhibit an overall increase with the lapse of time for reasons such as a temperature increase in the Imagent equipment.

In such a case, the increase of intensity can be reduced through the use of a second polynomial line fitting.

An overall increase or decrease phenomenon can be removed using the difference between raw data and a fitting line. Moreover, an approximation to the original intensity value can be enabled by adding the average value of raw data again.

The signals of concentration changes using an altered Beer–Lambert law appear in the form of containing a large amount of high-frequency substances. As a result, as shown in Figure [5], low-frequency filtering was performed with a cut-off frequency of 0.125 Hz in order to obtain a cleaner
The concentration changes calculated from HbO2 and Hbr were different. The initial values of concentration changes in each channel or trial were also different. Therefore, an offset was set up so as to adjust the initial value of concentration changes at each trial. The point of stimulation was set at zero seconds. Using the average gap in concentration changes between the post-stimulation line and the pre-stimulation base line during the time of –25 to –5 seconds, the initial gap in concentration changes was reduced for each trial.

C. Setting up features and decoding

The average and standard deviations of the concentration changes of HbO2 from the point of stimulation to 30 seconds after a round of trials are shown in Figure 4. Each odor stimulation produces a different time of maximum concentration change and a different change value. Therefore, decoding was performed using the maximum value of concentration changes for each odor stimulation. However, as the point to reach the maximum concentration change varies in each trial, it is difficult to provide high reliability, regardless of success rates. For this reason, this study set up a sliding window with a window size of three seconds and a center of 1.5 seconds, and thereby set the average of concentration changes as a feature.

A probability density function was modeled using the Gaussian distribution. The probability density function based on the Gaussian distribution was formed as the below X equation.

\[
p(x_{n}(k)) = \frac{1}{\sqrt{2\pi\sigma_{n}^{2}(k)}} e^{-\frac{(x_{n}(k) - \mu_{n}(k))^{2}}{2\sigma_{n}^{2}(k)}}
\]

(7)

Here, \( k \) is the type of odor stimulation used in the experiment and \( n \) is the number of channel. \( \mu_{n}(k) \) is the average of the training data, \( \sigma_{n}^{2}(k) \) is the standard deviation of the training data.

To reversely infer the unknown chemical \( k \) using the probability density value of each chemical obtained from the Gaussian modeling, the maximum likelihood estimation technique was employed. The maximum likelihood estimation that maximizes \( p(x_{1}(k), x_{2}(k),...,x_{N}(k)) \), which is the probability density function of the unknown chemical \( k \), is as follows.

\[
\hat{k} = \arg\max_{k} p(x_{1}(k), x_{2}(k),...,x_{N}(k))
\]

(8)

If each channel is assumed to be probabilistic and independent from the others [5],[6], an equation can be developed, as follows.

\[
p(x_{1}(k), x_{2}(k),...,x_{N}(k)) = \prod_{n=1}^{N} p(x_{n}(k))
\]

(9)

\[
\hat{k} = \arg\max_{k} \prod_{n=1}^{N} p(x_{n}(k))
\]

(10)

This function can be viewed as a multidimensional entropy likelihood function to each chemical response. Maximum likelihood estimation is a nonlinear classification method that estimates the likelihood for every number of cases, and finds a value that generates the highest likelihood. The chemical that maximizes \( \hat{k} \) was estimated according to this. This study used only one out of a total of eight trials as the test data, and the remaining seven trials were used as the training data. With this combination, eight data sets were used to infer odorants.
III. RESULTS

A. Decoding using max peaks

Figure 4 shows that the concentration changes of blood flow in the MOB of rats vary according to different chemicals of odor stimulation.

![Graph showing concentration changes of blood flow](image)

Fig. 5 The average and standard deviations of the maximum values of concentration changes for 30 seconds after three types of odor stimulation.

Figure 5 confirms that maximum concentration changes vary according to odor stimulations. In addition, the average of the maximum concentration changes was set as a feature.

![Graph showing average and standard deviations](image)

Figure 6 shows the results when the Gaussian modeling was built based on the average and standard deviations of concentration changes at the point when the maximum concentration change occurred for 30 seconds after the stimulation point. Looking at the results of the Gaussian modeling in Hep, Ib, and Blank in Figure 6, it is easy to distinguish between Blank and Hep, but Ib exhibits a high probability of being classified as either Hep or Blank.

The performance of decoding when the maximum likelihood estimation technique was applied to the Gaussian model in Figure 6 is shown in Figure 7.

The Gaussian distribution suggested a relatively higher probability of the classification of Ib as Hep or Blank. Accordingly, the actual results of decoding confirmed that Ib has a lower performance compared to Hep and Blank, as shown in Figure 7. The overall performance of decoding was revealed to be high at 83.3%. However, when the average of the maximum values of concentration changes was set as a feature, the decoding results became without the consideration of time information, which increased the need to use a different feature.

![Graph showing decoding accuracy](image)

Fig. 7 Performance results of decoding when the maximum value of concentrations changes was set as a feature. As estimated from the model in Figure 6, the performance of Ib is the lowest among the three types of odor stimulation.

B. Decoding using the average of concentration changes according to the lapse of time

After odor stimulation, the concentration of HbO₂ was observed to increase with time, and then decrease after a certain lapse of time (Figure 4).

Based on this phenomenon, the earlier mentioned Gaussian modeling and maximum likelihood estimation were performed according to the lapse of time after odor stimulation by setting the average of HbO₂’s concentration changes as a feature while using a sliding window with a window size of three seconds and a center of 1.5 seconds. As the gaps in concentration changes among individual chemicals for about five seconds after odor stimulation, with an offset set up, are negligible, the odorants are hardly distinguishable. However, Figure 4 shows that the gaps in concentration changes among individual chemicals become greater with the passage of time, making the identification of odorants easier. Similarly, as the gaps narrow again, the identification becomes more difficult. The decoding performances based on each central time slot are presented in Figure 8. The decoding performance for 10.5 to 13.5 seconds is indicated at 92%. Meanwhile, the decoding success rate remained at about 40% from the point of stimulation to 4.5 seconds, suggesting difficulty in distinguishing among odorants. While the decoding performance from 13.5 seconds to 21 seconds appeared relatively high, the decoding performance from 22.5 seconds was observed to drop markedly.
Such findings confirmed that the highest decoding performance was realized around the time of 10 to 14 seconds.

IV. CONCLUSION

This study measured hemodynamic response changes occurring when odor stimulation was applied to the MOB of rats using NIRS. In addition, the concentration changes in HbO₂ and Hbr were calculated using the Beer–Lambert law. Meanwhile, this work performed an analysis using HbO₂ only, given that the concentration changes in Hbr were relatively smaller than in HbO₂.

The method of inferring odorants using the scale of concentration changes created high performances. However, this does not take into account time information, resulting in difficulty in increasing reliability. As a result, the inference of odorants with consideration of time information was performed. The experiment revealed that concentration changes reach their peak at around 15 seconds after odor stimulation, and then decline gradually. Based on this result, the actual performance of decoding was also expected to become highest at around 15 seconds.

The actual performance of decoding also confirmed the above assumption, generating the highest performance at around 15 seconds. Given the limitations of the present work, additional experiments are planned to increase the reliability of our findings by increasing the number of trials used for analysis.

REFERENCES


Fig. 8 Gaussian model using the average and standard deviations of the maximum values of concentration changes for 30 seconds after odor stimulation.
Landslide Hazard Mapping of Penang Island Using Decision Tree Model

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Abstract—Landslide hazard mapping using decision tree on Penang Island, Malaysia is proposed in this paper. Decision tree is one of popular classification algorithm of data mining. Decision tree was constructed using Quinlan’s algorithm C4.5 with 12 landslide-causative factors to produce landslide hazard maps. Hazard map that obtained using frequency ratio is improved by decision tree in term of the risk level where non-hazardous areas are reduced and others increase.

Keywords—Decision tree, landslide, hazard map.

I. INTRODUCTION

Landslide is a common disaster happening in the world. This geological phenomenon is natural hazards that often cause damages to society. Landslides occur when the stability of a slope changes from a stable state to an unstable state. Natural and human activities are the causes of landslides. In Malaysia, landslides are common especially during monsoon seasons from May to September and November to March. Damages due to landslide have been particularly high in the recent years from 2000 to 2009 (Lim et. al., 2011). Several attempts had been performed in order to reduce the damage caused by landslide by predicting the risky areas. Studies have been conducted to detect landslides and analyse the landslide hazard using the GIS and remote sensing [1], [2]. Various techniques have been implemented in the studies to obtain the landslide analysis.

In this paper, decision tree (DT) algorithm is used to produce the landslide hazard maps. DT is one of data mining approach which uses graphical model to describe decisions and its possible outcomes. DT is chosen because it does not require statistical assumptions and able to handle data that are represented on different measurement scales. Besides that, DT model could produce a result which is simple to understand and interpret due to its white box modelling nature.

II. STUDY AREA

The study area for this research is island of Penang state, Malaysia as shown in Figure 1. Penang is one of the 13 states of Malaysia located on North West of Peninsular Malaysia. The island is located within latitudes 5°15’N to 5°30’N and longitudes 100°10’E to 100°20’E. The average rainfall amount of Penang Island ranges from 2254mm to 2903mm annually. Elevation of the terrain is from 0 to 820 meters height above the sea level. The slope ranges from 0° to 87°. The vegetation that covers in Penang Island is mainly of forest and fruit plantations and the land use is consisted of forest, urban, grassland, plantation and lakes and rivers. There are fault lines that run from north to south in the centre of the island.

Table 1 The study area, Penang Island, Malaysia

III. DATA SET

Topographical, geological, soil map and various data on Penang Island were obtained from Meteorological Department, Penang Geographic Information System Center, Department of Survey and Mapping Malaysia, Department of Drainage and Irrigation Malaysia, Department of Agriculture and Mineral and Geoscience Department. From topographical database, digital elevation model with resolution of 5 meters is constructed in order to extract an elevation map. The curvature, slope angle and slope aspect are obtained from the elevation map. Distance from drainage, distance from road and distance from fault lines map obtained from their own digital map respectively. Land use map in Penang Island consists of 17 types of land usage such as transport,