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Possibility for Predicting the Evaluation of Product Price in the Prefrontal Cortex : A NIRS Study

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Abstract*— Neuromarketing, an actively studied field in recent years, uses measurements of brain activity to understand the purchasing motives of consumers. This field has expanded due to the development of noninvasive brain measurement techniques and newfound knowledge relating to human decision-making from the viewpoint of behavioral economics. Previous studies have indicated that activity in medial prefrontal cortex, medial orbitofrontal cortex, and dorsolateral prefrontal cortex react to reward and punishment, and thus may act as neurologic predictive factors concerning purchasing. This study focuses on price, which is one of a purchasing decision-making factor. We used near-infrared spectroscopy (NIRS) to measure brain activity changes induced by evaluation of product price. We determined the classification accuracy of price evaluation (i.e., subjects felt it was "expensive" or "inexpensive") offline using machine learning; the average overall accuracy was more than 75%. In addition, the rate of divergence between the product price and the price predicted by the subject was correlated with change in oxygenated hemoglobin concentrations. These findings suggest that brain activity can be used to evaluate the extent to which consumers feel a product price to be "expensive" or "inexpensive".

***Index Terms*—dorsolateral prefrontal cortex, neuromarketing, near-infrared spectroscopy, medial prefrontal cortex, decision-making.**

I. INTRODUCTION

Neuromarketing uses measurements of brain activity to understand the purchasing motives of consumers, and it has recently become an actively studied field [1,2]. It follows the development of (i) noninvasive brain measurement techniques and of (ii) behavioral economics. The first refers to techniques that are largely used for clinical diagnoses, enable observation of a local brain region without inflicting brain damage. Nowadays, such techniques have come to be applied to not only brain-computer interface (BCI) [3] but also marketing research. The latter refers to the study combining economics with psychology. Classical economics built its theory and model on the premise that humans display rational judgment. However, according to the framing effect [4] and prospect theory [5] proposed by behavioral economics, human decision-making involves not only rational judgment, but also emotion. Therefore, neuromarketing has arisen as a new tool to elucidate the psychological elements of decision-making, since it has already been shown that humans can be irrational when it comes to decision-making. For example, one study reported that images of culturally familiar brands are biased to evoke behavioral preferences [6], while another study showed that price differences can influence the pleasantness of a flavor even if quality is exactly the same [7]. Currently, it is known that the buying intention of a consumer is influenced by preference and product price. Studies on key brain regions involved in emotion processing, including preference, reward, and punishment systems, have received much attention. Previous studies have reported that preference elicits activation in the nucleus accumbens (NAcc), while excessive prices elicit insula activation and medial prefrontal cortex (MPFC) deactivation [8]. The ventral striatum and orbitofrontal cortex (OFC) regions are also involved in reward [9,10,11]. There is the research that OFC has a different role by each sub region; the lateral OFC (lOFC) and the medial OFC (mOFC) are together responsive to the rewarding and punishing values [12]. When receiving a reward, it has different types of value (i.e., outcome value, goal value and decision value) and also different types of costs (i.e., uncertainties, delays and effort requirements). However, mOFC reacts to any types of value regardless of whether they are actually experienced rewards or merely potential future rewards [13]. In addition, it has been suggested that the dorsolateral prefrontal cortex (DLPFC) may display neurologic predictive factors concerning purchase [14]. According to literature [15], the activity in DLPFC have been shown to be positively correlated with the appetitive values range, and also negatively correlated with the aversive values range. These functional modules related to decision-making are supported by distributed neural systems, which are distinct but largely overlapping, and linked by reciprocal interactions [16]. Various areas of the brain involved in cognitive behavior have been revealed, and attempts to predict preference and decision-making have increased [17,18,19]. With respect to human's preference, analysis of prefrontal areas identified the patterns of activation in MPFC in response to varying levels of preference in the literature[20], and made an attempt to distinguish between "attractive" and "unattractive" by brain information when subjects performed the task that elicit a preference in the literature [21]. Besides these, there is the research that decoded subject's decisions to a high level of accuracy on neural signals even before they were required to make a choice [22], and the another one demonstrated that the brain responses of a relatively small group of subjects were significantly correlated with the number of product units sold, they are also modestly predictive of population

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effects [23]. In addition, a model that discriminates preferred item based on brain activity, offering detailed information about it was reported [24].

In this study, we focused on price, an important factor in purchase decision-making. Subjects were asked to evaluate a product price while their brain activity was being analyzed by near-infrared spectroscopy (NIRS). Subjective price evaluation was classified as either “expensive” or “inexpensive” based on their internal reference price [25]. The ability to predict a consumer's evaluation of price can be applied to purchasing decision-making support systems for consumers as well as enable companies to set price. We examined whether changes in brain activity measured by NIRS could predict the evaluation of price by consumers.

II. METHODS

A. Subjects

We carried out the experiment twice, defined herein as 1st and 2nd experiment. Thirty-four students of the Faculty of Engineering at the University of Toyama participated in the experiment. Nineteen of these subjects, aged 21–23 years (mean age, 21.7) participated in 1st experiment, and fifteen subjects aged 21–25 years (mean age, 21.6) participated in 2nd experiment were right-handed, with the exception of one left-handed subject in each experiment. Informed consent was obtained from all participants, and they were informed of their right to withdraw from the experiment at any time.

B. Task Design

For this study, we designed a task in which subjects can feel the price of a product as “expensive” or “inexpensive” (price valuation task). The aim of the price valuation task is to make subjects evaluate price unconsciously; therefore, when performing the task, subjects are not aware the experiment intended to evaluate price; at the end of each trial, subjects were asked to predict the product price. Figure 1 shows the scheme of the price valuation task.

Step 1. To stabilize subject’ brain activity, a cross was displayed on the center of the screen during the first rest period (approximately 10 s).

Step 2. The product and simple information regarding the product (i.e., manufacturer, capacity, and production areas) were displayed on the screen. Subject then predicted product price (approximately 10 s).

Step 3. The subject was given a second rest period, similar to Step 1 (approximately 10 s).

Step 4. The price of the product shown in Step 2 was displayed (approximately 10 s).

Step 5. The subject then input the price predicted in Step 2. The screen went back to Step 1 soon after this input.

We used 55 product images as stimuli, and the sequence through Step 1-Step 5 conducted 55 times constituted 1 trial. During each trial, product images were presented at random. These products were familiar items that subjects were expected to know the price as much as possible, such as stationery (e.g., notebook, mechanical pencil, or eraser), daily necessities (e.g., tissue, detergent, or toothbrush), and food (e.g., vegetables, juice, or snacks). The product information was referred from the official homepage of the manufacturer. The prices shown in Step 4 were randomly set to 0.5-2 times the real price in 1st experiment and set to 0.3-1.7 times the real price in the 2nd experiment so that subjects could naturally regard the product price as more “expensive” or “inexpensive” in 1st and 2nd experiment, respectively.

C. Measurement of Brain Activity

In this experiment, NIRS was used to measure brain activity during task. NIRS estimates change in blood hemoglobin (Hb) concentrations by measuring change in the amount of near-IR light entering and returning from the brain, through the near-IR light absorption characteristic of Hb. Change in oxygenated Hb (oxy-Hb) concentrations and deoxygenated Hb (deoxy-Hb) concentrations are measured by NIRS. There are a number of noninvasive measurement techniques of brain activity other than NIRS: electroencephalography (EEG), magneto encephalography (MEG), and functional magnetic resonance imaging (fMRI) are some of the most employed.

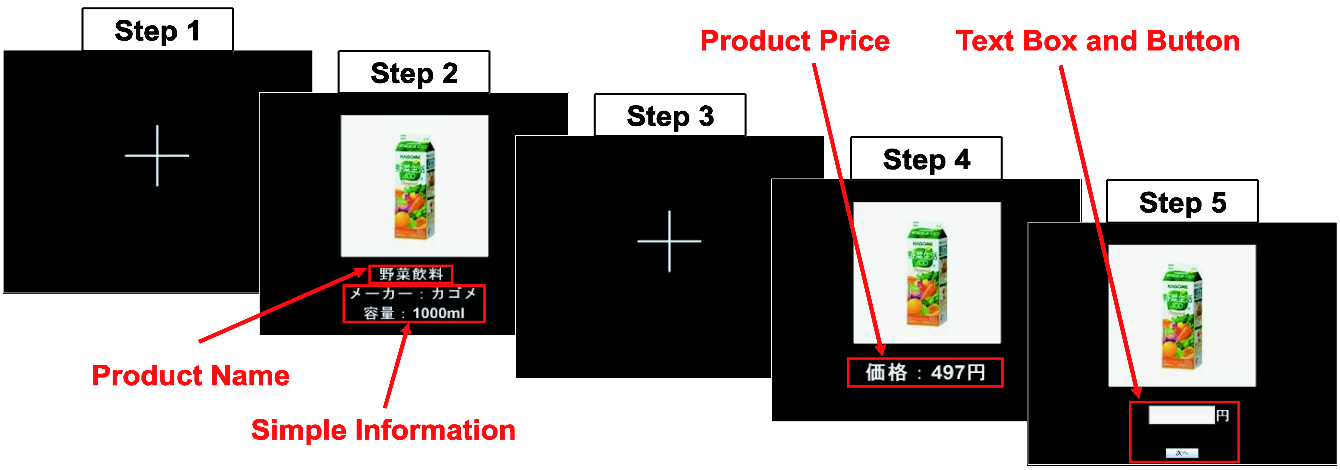

Fig 1: Price Valuation Task. In this task flow, subjects saw a cross (Step 1; 10 s), saw the product’s simple information and then predict

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EEG uses electrodes applied to the scalp to measure changes in the electrical field in the brain regions underneath. Similarly, MEG measures changes in the magnetic fields induced by neuronal activity. Both techniques present very high temporal resolution and can therefore detect brief neuronal events, but their low spatial resolution, dependent on the number of electrodes used, makes it difficult to estimate the precise origin of the electromagnetic events observed. fMRI measures the blood oxygenation level – dependent (BOLD) signal based on specific magnetic characteristic. It has high spatial resolution, but as fMRI observes a secondary phenomenon—blood flow fluctuations caused by neural activity—temporal resolution is low. Moreover, fMRI is limited portability and needs high set-up and maintenance costs, user is both restricted and forced to lie down. Although inferior to EEG and MEG in terms of temporal resolution, NIRS is superior in spatial resolution, and it is less influenced by electrical noise than EEG. Moreover, since NIRS is portable and presents fewer restrictions to its use than fMRI, it is a good option for measuring brain activity during usual behavior such as decision-making. The acquisition of NIRS signal was conducted on an OEG-16 (Spectratech Inc., Yokohama, Japan), which included an optode sensor set consisting of 6 light emitters and 6 photo detectors arranged at 3 cm intervals in a matrix form. Therefore, we measured the prefrontal region in a total of 16 channels, as shown in Fig. 2. Two different near-IR light wavelengths, 770 nm and 840 nm, were used. The sampling interval was 0.65 s (frequency bands 0.75 Hz) in 1st experiment and 0.08 s (frequency bands 6.10 Hz) in the 2nd experiment. Sampling interval in 2nd experiment was changed by upgrade of the version of OEG-16. The specifications are the same as those of OEG-SpO2 (Spectratech Inc., Yokohama, Japan). Numbers in the figure depict channel number. The red channels (6ch, 7ch, 8ch, 9ch, 12ch, 13ch, and 14ch) correspond to MPFC, mOFC, and DLPFC, brain areas involved in reward and punishment processing and measured as the target channels. The correspondence between channels and brain regions was based on the literature [14].

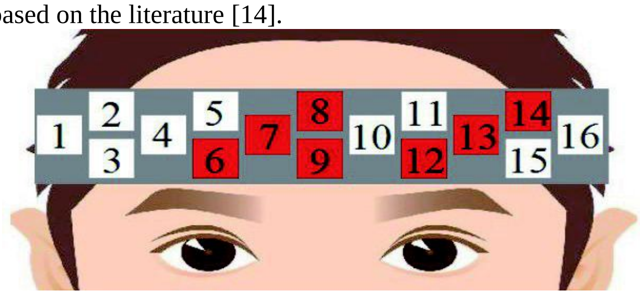

Fig 2: Measurement sites. The channels located in the prefrontal regions. The red channels (6ch, 7ch, 8ch, 9ch, 12ch, 13ch, and 14ch) correspond to MPFC, mOFC, and DLPFC, brain areas involved in reward and punishment processing and measured as the target channels.

III. DATA ANALYSIS

A. Preprocessing

NIRS data is influenced by artifacts extraneous to brain function, such as cardiac beat and respiratory signal, blood pressure change and subject motion and so forth. In order to remove physiological noise, we carried out data smoothing processing prior to the analysis. In 1st experiment, Savitzky-Golay smoothing filter [26] was applied. This filter set the base point to smoothing from data, and calculates the M-order polynomial approximation by the least squares method by using N points in front and rear adjacent to the base point. Whole data is smoothed by sequentially repeating the above process in shifting the base point in time series order. N is amount of data and M is order. In this study, we set the parameters M=5 and M =2 .

This method has the advantage of keeping the peak positions and amplitude of data. In 2nd experiment, low-pass filter was applied. With the upgraded version of OEG-16, we became able to obtain the data around the 1 Hz frequency band, which is easily contaminated by artifacts such as pulsation. Therefore, the cutoff frequency was set to 0.75 Hz, thus eliminating a high frequency noise component. Then, the smoothed data was carried out the base processing. The base processing is a method to represent more clearly the state of brain activity by shifting a particular base point to zero. In this experiment, the base point was set at the one sampling point prior to Step 4 (the last sampling point of Step 3), in order to emphasize the brain activity during the evaluation of price, and base processing was carried out using approximately 10 s data from Step 4 (1st experiment: approximately 10 s = 16 samplings; 2nd experiment: approximately 10 s = 128 samplings).

B. Support vector machine

For the learning and classification approach, we used support vector machine (SVM) [27]. SVM is a 2-class pattern recognition technique, i.e., it performs a binary classification of the sample. The learning data of the nearest neighbors from the decision boundary for each class is called support vector. The decision boundary is decided by maximizing the distance (margin) between the decision boundary and the support vector. In this study, we implemented the SVM classifier using the LIBSVM package. The kernel function used the Gaussian kernels. LIBSVM has two standard cost parameters, which are called c and σ, and obtained the optimum parameters by grid search. c was set in the range of 0.01, 0.1, 0.5, 1.0, 5.0, 10, 100, 1000, 10000 and σ was set in the range of 0.01, 0.1, 0.5, 1.0, 5.0, 10, 100, 1000, 10000. The feature for learning and classification used the mean change in oxy-Hb concentrations during Step 4, when subjects were evaluating the price unconsciously.

IV. RESULTS

A. Behavioral Results

In this study, subjects' evaluation of price was obtained by comparing the price subjects predicted during Step 2 (predicted price) with the price shown during Step 4 (presented price). We obtained 55 samples per subject in this study, and divided them into two classes, "expensive" (predicted price inferior to presented price) and

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"inexpensive" (predicted price superior to presented price). In case the predicted price was the same as the presented price, the sample was excluded from further analysis. In 1st experiment, the "expensive" class had an average of 37.5 (SE = 0.93) samples and the "inexpensive" class had an average of 17.3 (SE = 0.94) samples. In 2nd experiment, the "expensive" class had an average of 32.9 (SE = 0.89) samples and the "inexpensive" class had an average of 21.9 (SE = 0.88) samples. Since the presented price was randomly set to 0.5-2 times the actual price in 1st experiment, the experiment was biased toward "expensive" samples. While 2nd experiment, the bias was improved slightly by setting the presented price to 0.3-1.7 times the actual price.

B. Neural Results

Results are shown for trends in brain activity during the evaluation of price and for classification accuracy between "expensive" and "inexpensive". When we classified the change in oxy-Hb concentrations during Step 4 into two classes and calculated the statistical differences between the two, approximately two-third of the subjects had significantly different channels within the target channels. As some subjects presented positive or negative correlation between change in oxy-Hb concentrations and the rate of divergence, it was possible to predict the extent to which consumers judge a product price "expensive" or "inexpensive" by measuring their brain activity. Finally, we analyzed classification accuracy using support vector machine (SVM), obtaining an average accuracy of 76.7%. This finding suggests this approach allows classification of both classes with high probability.

1. Significantly Difference Activity

In order to observe brain activity during the evaluation of product price, the change in oxy-Hb concentrations during Step 4 were divided into two classes, "expensive" and "inexpensive", and average values and standard error were calculated in each channel for each subject. To calculate the average, only data with significant degree of divergence between the predicted price and the presented price was used. We defined the divergence index as the rate of divergence. Rate of divergence lower than 20%, i.e., a divergence in the range of 0-20% within the "expensive" class and 20-0% within the "inexpensive" class, was defined as small divergence, and excluded from further analysis. However, since such exclusion of data from the "inexpensive" class would render the number of data of some subjects lower than 20, no exclusion was applied in "inexpensive" class. The rate of divergence is explained in detail in the next subsection, 2.

Figure 3(a) and 3(b) show example results in 1st experiment. Figure 3(c) and 3(d) show example results in 2nd experiment. The vertical and horizontal axes of the graphs represent change in oxy-Hb concentrations and time series, respectively. The blue and green waveforms represent the average waveform of the "expensive" and "inexpensive" classes in the time series. The error bars indicate the standard error. Statistically significant differences between the two classes were examined by t-test. The vertical line represents the results of the t-test; the red, pink and aqua lines indicate $p < 0.01$, $p < 0.02$, and $p < 0.05$, respectively. It can be seen that 23 of the 34 subjects had significantly different channels within the target channels.

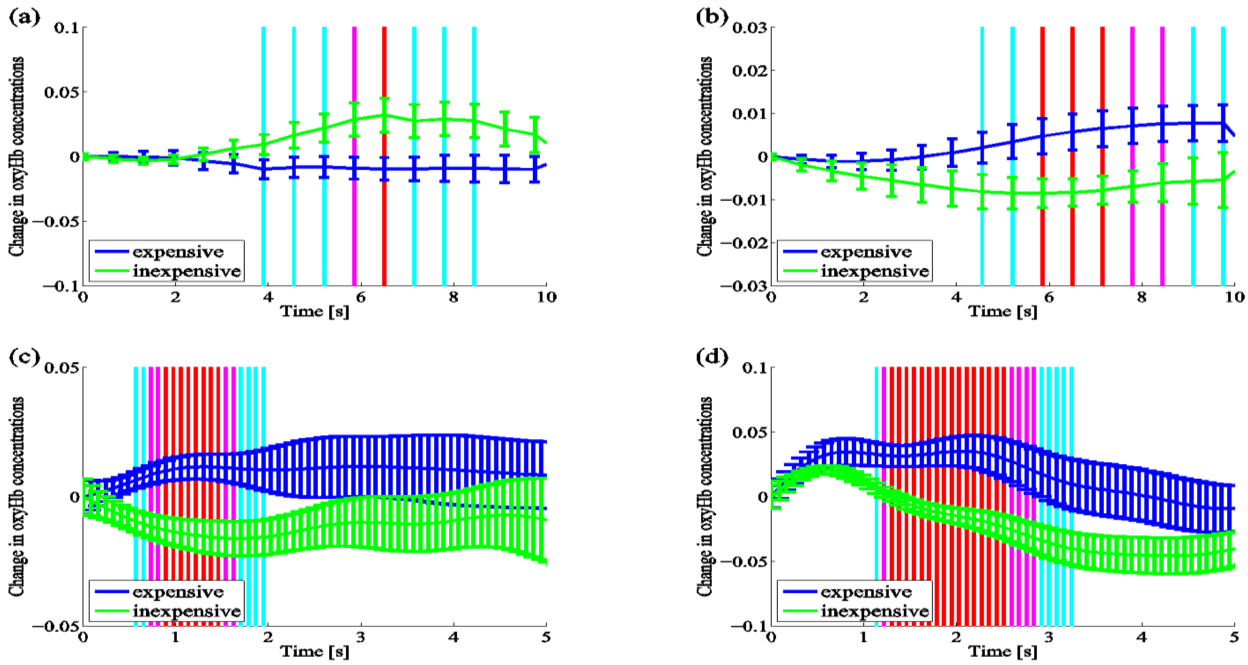

Fig 3: Average waveform for "expensive" versus "inexpensive". (a) The brain response in 9ch for subject 3; (b) The brain response in 12ch for subject 15; (c) The brain response in 14ch for subject 20; (d) The brain response in 7ch for subject 26. The figures indicate the averaged time course of change in oxy-Hb concentrations during Step 4 in significantly activated channels. The vertical lines represent the results of the t-test; the aqua line, p < 0.05; the pink line, p < 0.02; the red line, p < 0.01. Error bars denote standard error.

2. Relationship with Rate of Divergence

We analyzed the presence of an association between the magnitude of brain activity and the rate of divergence. The rate of divergence is an index of the divergence between the predicted and presented price, and it is defined in the following equation:

$$\text{rate of divergence}[\%] = \frac{\text{presented price} - \text{predicted price}}{\text{presented price}} \times 100 \qquad (1)$$

So, if the subject has expected a product price of 100 yen (predicted price = 100 yen) and according to product information it cost 200 yen (presented price = 200 yen), then, the rate of divergence was 50%. Hence, it follows that the subject considered the product 100 yen (50% of the presented price) more expensive than the predicted price. This divergence can be represented quantitatively by using the rate of divergence. Figure 4 shows a scatter diagram depicting the average of change in oxy-Hb concentrations by rate of divergence. Briefly, the data point on the graph indicates the average of the average waveform divided in 5% intervals of the rate of divergence (the divided data is change in oxy-Hb concentrations during Step 4. The vertical and horizontal axes of the graph represent change in oxy-Hb concentrations and rate of divergence, respectively. The linear regression line and R-squared are shown in each scatter diagram. Figure 4(a) and 4(b) show example results in the "expensive" class. Figure 4(c) and 4(d) show example results in the "inexpensive" class. The rate of divergence in the "inexpensive" class is the absolute value. Figure 4(a) depicts a somewhat positive correlation (R^2 = 0.382) and 4(b) depicts a negative correlation (R^2 = 0.571). Figure 4(c) depicts a negative correlation (R^2 = 0.574) and 4(d) depicts a positive correlation (R^2 = 0.524). Therefore, we suggest that brain activity can be positively or negatively modulated in proportion to the magnitude of the divergence between the predicted and the real price of a product.

3. Classification Accuracy

We analyzed the classification accuracy between "expensive" and "inexpensive" offline using SVM. Approximately 55 sample data were obtained per subject (if the presented price was the same as the predicted price, the sample was excluded.). We validated the classification accuracy using 5-fold cross validation. The feature was the average change in oxy-Hb concentrations during Step 4. There are two ways of selecting the factor for SVM: channel non-selection and channel selection. Channel non-selection is a seven-dimensional feature vector composed of all target channels, while channel selection is a one-to even-dimensional feature vector composed of round robin-selected channels from the target channels.

Table 1 shows subjects' average highest accuracies for each experiment. Regarding the result of channel non-selection, the average accuracy was 71.8% in 1st experiment and 62.4% in 2nd experiment;

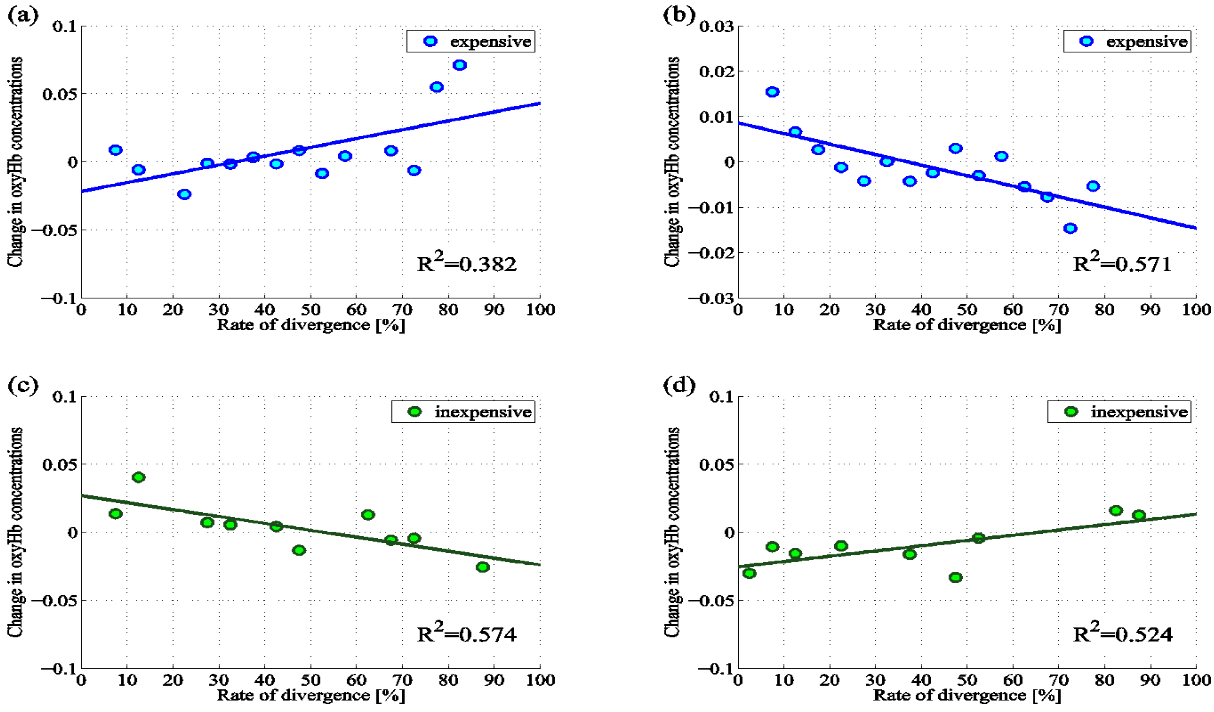

Fig 4: Correlation between change in oxy-Hb concentrations and rate of divergence. (a) Positive correlation shown in "expensive" class in 7ch for subject 4; (b) Negative correlation shown in "expensive" class in 8ch for subject 5; (c) Negative correlation shown in "inexpensive" class in 14ch for subject 9; (d) Positive correlation shown in "inexpensive" class in 32ch for subject 6. The scatter diagrams are the example of result in the "expensive" and "inexpensive" class, which depict correlation between the average of change in oxy-Hb concentrations and rate of divergence. The linear regression line and R-squared are indicated on the graph.

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Total accuracy was 67.6%. Regarding the result of channel selection, the average accuracy was 80.1% in 1st experiment and 72.3% in 2nd experiment 2; total accuracy was 76.7%. Accuracy was higher for channel selection than for channel non-selection, but both results exceeded chance level. However, confidence intervals depend on the number of trials, and when the number of trials is small, as in the present study, chance level needs to estimate the higher one. When compared with the chance level (20 trials/class, 2-class) [28], which took into account a confidence interval with a significance level of 1%, only channel selection exceeded it. Channel non-selection exceeded the chance level (20 trials/class, 2-class) for the confidence interval with a significance level of 5%. This finding suggests this approach is able to classify both “expensive” and “inexpensive” classes with high probability based on brain activity.

Table 1: Table 1: The table shows the average of the classification accuracy between “expensive” and “inexpensive” separately for channel non-selection and channel selection for each experiment.

Experiment	Highest Accuracy (%)	
	Channel non-selection	Channel selection
1st Experiment	71.8	80.1
2nd Experiment	62.4	72.3
Total Average	67.6	76.7

V. DISCUSSION

To analyze the brain activity during the evaluation of price, the average waveform and the standard error for the two classes, “expensive” and “inexpensive”, are shown in the graphs. As shown in the Fig. 3, brain activity differs between subjects in the “expensive” and “inexpensive” condition. Figure 3(b), 3(c) and 3(d) depict a trend towards activation at a peak period of 3-7 s in subjects in the “expensive” condition. Figure 3(a) shows the trend towards inactivation in subjects in the “inexpensive” condition. Since the pattern of increase or decreases change in oxy-Hb concentrations present individual differences, the response was reversed in Fig. 3(b). In both cases, as was confirmed by the t-test, it is possible to separate the data in the “expensive” and “inexpensive” conditions. However, the analysis of the complete sample shows that brain activity needs to be learned for each person when estimating the evaluation of price, because there are individual differences in the brain activity pattern and peak response causing the presence of statistically significant differences not be consistent within channels. We compared the classification accuracy between channel non-selection and channel selection offline using SVM, to examine the influence of the individual differences described above. As a result, the classification accuracy; total average was 67.6% in channel non-selection, and 76.7% in channel selection. Therefore, this result shows that the accuracy is approximately 10% higher when using channels selected to take into consideration subjects’ individual differences than using all target channels. In addition, as channel selection exceeded the chance level (20 trials/class, 2-class) when confidence interval was set to a significance level of 1%, high accuracy can be expected with a 2-class classification offline. Next, we analyzed the association between change in oxy-Hb concentrations and the rate of divergence. As shown in Fig. 4, there were both positive and negative correlations between change in oxy-Hb concentrations and the rate of divergence. We believe the correlation direction was inconsistent within the same class due to individual differences in the brain activity patterns, as explained in section Ⅳ.B.1. In a number of subjects, though, no correlation was found; it is possible that this correlation should emerge with the combination of channels and the plotting of data on multidimensional space. Based on these results, we believe it is possible to predict the extent to which consumers feel a product to be “expensive” or “inexpensive” by measuring their brain activity. Moreover, their judgment was not limited to the 2-class classification. When constructing a price valuation system, it is difficult to make a model able to fit all users, because there are individual differences across NIRS data during the evaluation of price and there are not trends in brain activity common to all subjects. Therefore, using a machine-learning approach that learns from the pattern exhibited by each subject may be a better means of constructing a system under the present circumstances. This experiment required 1 h per subject for data collection, so the burden on users in case of actual data collection is assumed to be same. Compared with general marketing methods, such as consumer questionnaires, this method is not considered to be more demanding.

In case the system interface performs a 2-class classification such as “expensive” and “inexpensive”, the SVM learning model applied in this study is assumed useful. However, in case the system interface estimates specific values, such as the divergence between the predicted and presented price, this learning method needs to be more thoroughly examined. According to the prospect theory, in case of monetary choices it has been shown that individuals weigh losses more strongly than gains of a similar magnitude [5]. It is thought that the cause of this asymmetry is the existence of a separate valuation system within brain [15]. Since the magnitude of the increase or decrease in gain and loss is asymmetrical and nonlinear, it is believed that a model consisting of a 2-class classification, which independently learns by nonlinear machine learning, is beneficial.

VI. CONCLUSION

In this study, we focused on price, which is a purchasing decision-making factor. We used NIRS to measure brain activity of thirty-four students in price valuation task. We analyzed brain activity during the evaluation of price and classified the 2-class evaluation. We validated the classification accuracy using SVM; the total average was 76.7% in channel selected. This accuracy exceeded the chance level, which took into account the confidence interval, so that it can be said to be a 2-class classification with high probability. Moreover, since we found a correlation between change in oxy-Hb concentrations and the rate of divergence, there is a possibility to be able to predict the extent to which consumers judge a product price "expensive" or "inexpensive", not limited to a 2-class classification.

For the future, our group seeks to determine the classification accuracy of other techniques, such as the hidden Marko mode [29], a probabilistic model. Furthermore, we seek to predict the rate of divergence using multiple regression analysis and neural networks, aiming at building a practical prediction model. In addition, by measuring the subject's gaze using eye tracker, we seek to reveal as many facts as possible about brain activity of multiple purchase decision-making factors, such as relationship between preferences and prices.

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