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Estimation of force direction from functional near-infrared spectroscopy signals using sparse logistic regression.

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***Abstract*— The brain-machine interface (BMI) has been used as a communication tool for a person who has lost body function. Extracting functional information from brain signals is important for controlling a BMI in a realistic and natural way. For a BMI, a pattern classification algorithm, such as linear discriminant analysis (LDA) and support vector machine (SVM), has commonly been used. However, the classifier using brain signals tends to suffer from overfitting because there are too many obtained features compared with the number of samples. On the other hand, sparse logistic regression (SLR), which has been proposed as a new pattern classification method for brain signals, can select small number of features to classify and interpret brain functions. Thus, overfitting can be prevented using SLR. In this study, we measured functional near-infrared spectroscopy (fNIRS) signals during isometric arm movements in four directions and performed direction classification. The features to classify force direction were selected from obtained data sets using SLR and were used in a SVM. We compared the types of fNIRS signals (OxyHb and DeoxyHb) and feature selection methods. As a result, the classification accuracy was highest when both OxyHb and DeoxyHb were used as the features and both time and channel were selected. The peak time of the signal, when the task ends, and a few seconds after the task ends, were particularly well selected.**

I. INTRODUCTION

The brain-machine interface (BMI), which enables external devices to be directly controlled by brain signals, has been actively studied in recent years. Detailed analysis of the underlying brain signals related to specific movements is important for controlling a BMI in a realistic and natural way. Previous studies on brain function have shown that it is possible to estimate from brain signals by using pattern classification and decoding [1] [2]. Thus, the BMI is a promising communication tool for a person who has lost body function due to an injury or a disease such as amyotrophic lateral sclerosis (ALS).

Noninvasive neuroimaging techniques include electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS). fNIRS measures the concentration changes in oxygenated hemoglobin (OxyHb) and deoxygenated hemoglobin (DeoxyHb) in cerebral blood flows, which may be associated with neural activity. Unlike EEG, fNIRS is robust against electrical artifacts. Additionally, the fNIRS system is simple compared with the fMRI one. It is thus advantageous for measuring brain function in daily life.

When performing pattern classification, machine learning techniques, such as linear discriminant analysis (LDA) and support vector machine (SVM), have commonly been used. In experiments measuring brain activity, there were too many obtained features compared with the number of samples and the classifier is prone to overfitting. To solve this problem, sparse logistic regression (SLR) has been proposed recently. SLR is able to reduce the ineffective features to classify. This feature selection can prevent overfitting and estimate brain function that contributed to the classification. This method has been applied to discrimination of visual images from fMRI signals [3] and estimation of finger pinch force from fNIRS signals [4].

Previous studies show that it might be possible to estimate the arm force direction from fNIRS signals [5] [6]. However, investigation of the force directional information in fNIRS signals was insufficient. In this study, we further investigated this question by using SLR. In addition, we show that the classification accuracy can be improved by using the selected features of SLR into SVM.

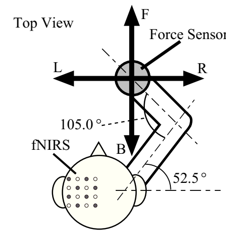

Fig. 1. Experimental setup.

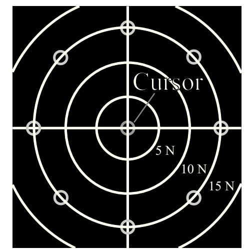

Fig. 2. Visual force feedback.

II. EXPERIMENTAL METHODS

This study was approved by the ethics board of the Nagaoka University of Technology. Four healthy men assented to and participated in the experiment. The task was an isometric muscle contraction with a force of 15 [N] in one of four directions: forward (F), backward (B), right (R), and left (L) (Fig. 1). For right arm force measurement, we used a six-axis force sensor (1FS-67M25A25-140, Nitta Corp, Japan). The sampling period was 5 [ms].

To control the posture of the subjects during the tasks, they were strapped to the chair with a belt. The heights of the chair and armrest were set so that the right arm was parallel to the upper surface of the desk. A force sensor was set at the hand position, and the angle of the right arm was 105° as shown in Fig. 1.

Visual feedback was displayed on the screen to the subject

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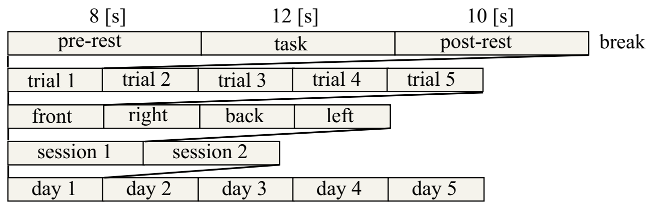


Fig. 3. Experimental task design.

as shown in Fig. 2. The small circle at the center represented the cursor, which moved in response to input signals from the force sensor. The cursor was blue when the force was less than 14 [N], yellow when it was 15 ± 1 [N], and red when it was more than 16 [N]. The screen displaying the feedback was placed at the center of the subject's visual field to avoid the need for eye movement. The distance from the subject's eyes to the display was set to 95 [cm]. The cursor diameter was 1.5 [cm] and the 15 [N] circle diameter was 25 [cm].

While the subject was doing the task, brain activity was measured by fNIRS. To measure the brain activity during right arm movement, fNIRS probes (to measure 24 channels) were placed around C3 of the international 10-20 system to cover the primary motor cortex of the left hemisphere. For fNIRS measurement, we used a near-infrared imaging device (OMM-3000, Shimadzu Corp, Japan). The sampling period was 130 [ms].

The experimental task design is shown in Fig. 3. The subjects performed the experiment over the course of five days. Two sessions were done per day. A session consisted of four blocks, and a block consisted of five trials for the same force direction. A trial consisted of an 8 [s] pre-rest, a 12 [s] task, and a 10 [s] post-rest. A total of 200 trials were conducted in five days (50 trials for each direction). To prevent inter-trial interference, a 30–60 [s] rest was given between trials, and the next trial started after stabilization of the fNIRS signals. The subject was verbally notified of the force direction at each block end.

III. ANALYSIS

A. Pre-processing

We set the start time (0 [s]) as the time when the force reached 3 [N] and set the end time as when it fell below 3 [N] to exclude differences in the start time between trials. All data sets for each subject were evaluated by multiple comparison of the force values. Data sets in which values were significantly different from the average were not used in the analysis. The force data used for the comparisons were the average value from the start to the end of the movement. The multiple comparison was performed using the Tukey-Kramer method with the significance level set to 1%. On average, 185 trials used in the analysis.

To remove noise in fNIRS signals, a gaussian temporal filter (full width at half maximum is 1 [s]) was used. To evaluate the concentration changes in hemoglobin between rest and task, the mean value during pre-rest was subtracted from the original signals. For the input features of the classifier, temporal data of 18 [s], which was 6 [s] after the end of the start movement, was used.

B. Classification

SVMs were used to estimate arm force direction. Three different classifications were performed: FB-RL, which classifies FBRL data into FB class and RL class, F-B, which classifies FB data into F class and B class, and R-L, which classifies RL data into R class and L class. This method required fewest classifiers when classifying four direction data into four classes.

Measurement of OxyHb by fNIRS signals is often used for the interpretation of brain function. However, DeoxyHb may also provide brain information. Therefore, in this study, we investigated and compared three types of fNIRS signals; only OxyHb, only DeoxyHb, and both Hb.

If we select only force directional information from fNIRS signals, the classification accuracy of the classifier should be improved. In this study, we used SLR to select features then force direction was estimated by SVM using the selected features. By comparing the classification accuracy of SVM, we investigated whether the force directional information is contained in the selected features. Five-fold cross-validation was repeated 20 times, and the mean value of classification accuracy (total is 100 times) was used to evaluate force directional information.

1) Support Vector Machine: In the SVM model, the discriminant function is

$$f(\mathbf{x}) = \operatorname{sgn}\left(\sum_{i=1}^{\ell} y_i \alpha_i^* K(\mathbf{x}, \mathbf{x}_i) + b^*\right), \tag{1}$$

where $\mathbf{x}_i$ are the training data sets, y_i are the desired outputs, and K is the kernel function. The α_i^* are defined using a quadratic programming problem.

$$\begin{aligned} &\text{max.} \quad W(\boldsymbol{\alpha}) = \sum_{i=1}^{\ell} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{\ell} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j). \\ &\text{sub. to} \;\; 0 \le \alpha_i \le C, \quad i = 1, \ldots, \ell, \quad \sum_{i=1}^{\ell} \alpha_i y_i = 0. \end{aligned} \tag{2}$$

C is an appropriate positive penalty parameter. When the sets of support vectors I are $0 \le \alpha_i^* \le C$, the threshold level b^* is given by the following equation.

$$b^* = \frac{1}{|I|}\sum_{i \in I}\left(y_i - \sum_{j=1}^{\ell} y_j \alpha_j^* K(\mathbf{x}_i, \mathbf{x}_j)\right). \tag{3}$$

Sequential minimal optimization (SMO) was used to solve for α_i^* and b^*. The linear kernel function is

$$K(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{x}_1^T \mathbf{x}_2. \tag{4}$$

2) Sparse Logistic Regression: In the SLR model, the linear discriminant function separating two classes is represented by the weighted sum of each feature value:

$$f(\mathbf{x}; \boldsymbol{\theta}) = \sum_{d=1}^{D} \mathbf{x}_d \theta_d + \theta_0, \tag{5}$$

where $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_D)^t$ is the input feature vector and $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_D)^t$ is the weight vector. The possibility that the input vector belongs to class C is given by

$$p = \frac{1}{1 + \exp(-f(\mathbf{x}; \boldsymbol{\theta}))} \equiv P(C|\mathbf{x}). \quad (6)$$

Given N input-output data samples, the likelihood function is expressed as

$$P(y_1, \ldots, y_N | \mathbf{x}_1, \ldots, \mathbf{x}_N; \boldsymbol{\theta}) = \prod_{n=1}^{N} p_n^{y_n} (1-p)^{1-y_n}, \quad (7)$$

where y_n is a variable such that $y = 0$ if the sample belongs to class 1 and $y = 1$ otherwise. The $\boldsymbol{\theta}$ that maximizes the likelihood is calculated in two steps.

$\boldsymbol{\theta} step$:

$$E(\boldsymbol{\theta}) = \sum_{n=1}^{N} \left\{ y_n \boldsymbol{\theta}^t \mathbf{x}_n - \log(\exp(\boldsymbol{\theta}^t \mathbf{x}_n)) \right\} - \frac{1}{2} \boldsymbol{\theta}^t \bar{A} \boldsymbol{\theta}, \quad (8)$$

$\alpha step$:

$$\bar{\alpha_d} = \frac{1 - \bar{\alpha_d} s_d^2}{\bar{\theta_d}^2}, \quad (9)$$

where $\bar{A}$ is a diagonal matrix whose diagonal elements are represented by $\bar{\alpha_d}$. Most of the estimated α_d diverges to infinity, and the corresponding weights $\boldsymbol{\theta}$ become zero through iteration of the two steps above. As a result, most of the features were eliminated, and we obtained a sparse model.

C. Feature Selection with SLR

SLR can only select features that contribute to the classification from the vast amount of features. However, the number of features in the time dimension selected by SLR are very few, which was about 10-20. Therefore, we selected features by the method shown in Fig. 4. First, feature selection was performed by SLR for 100 data sets (feature dimension is 18 [s] $\times$ 24 ch) that were created by five-fold cross-validation repeated 20 times. Then, the frequency of feature selection was obtained by counting the number of selections for each feature. In addition, the selection rate of each time was obtained by summing the count number in the channel dimension, and the selection rate of each channel was obtained by summing the count number in time dimension. In this study, to investigate where the force directional information is in the feature space, we performed three types of selection: time selection to select only the time (selected feature dimension is selected times $\times$ all channels), channel selection to select only the channel (selected feature dimension is all times $\times$ selected channels), and direct selection to select the time for each channel. The threshold of time selection was 30 [%] of the selection rate, threshold of channel selection was 30 [%], and direct selection was each feature more than twice, was used as input to SVM.

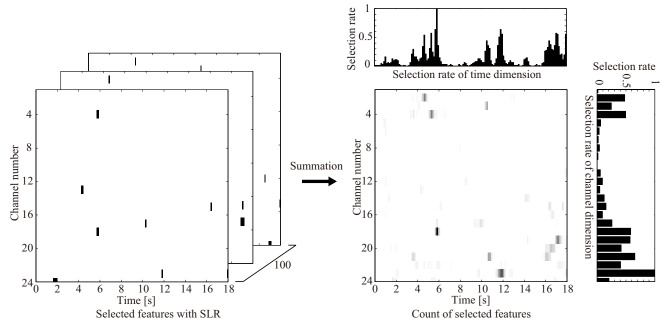


Fig. 4. Features selection methods.

IV. RESULTS

Table I shows the classification accuracy on average of all subjects for each method. Table II shows the number of input features for classification.

Comparing the type of input features, the classification accuracy was in the order of DeoxyHb < OxyHb < both Hb. Interestingly, for the combination of OxyHb and DeoxyHb, which has a low classification accuracy, the accuracy was further improved by a few %.

Comparing the classification methods, the classification

TABLE I

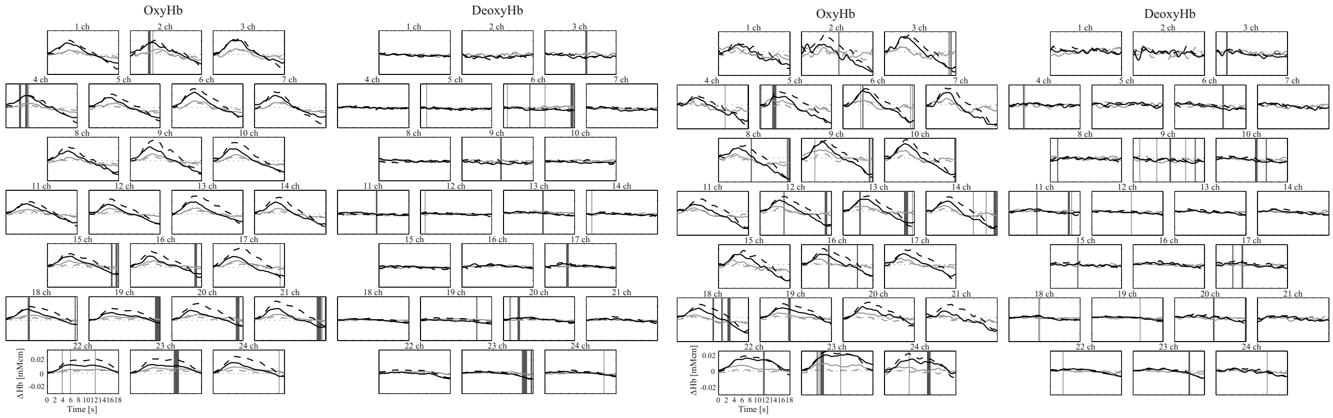
CLASSIFICATION ACCURACY ON AVERAGE OF ALL SUBJECTS.

Methods	OxyHb			DeoxyHb			Both Hb		
	FB-RL [%]	F-B [%]	R-L [%]	FB-RL [%]	F-B [%]	R-L [%]	FB-RL [%]	F-B [%]	R-L [%]
SVM	90.05	61.94	72.97	77.88	60.46	62.22	90.18	64.80	73.87
Time selection	90.43	65.28	75.80	79.56	69.46	69.51	90.57	71.09	75.89
Channel selection	91.01	65.46	75.34	79.32	67.36	70.87	92.34	72.36	79.42
Direct selection	97.27	92.25	95.06	95.06	95.54	96.71	98.58	96.72	98.37

TABLE II

NUMBER OF INPUT FEATURES ON AVERAGE OF ALL SUBJECTS.

Methods	OxyHb			DeoxyHb			Both Hb		
	FB-RL	F-B	R-L	FB-RL	F-B	R-L	FB-RL	F-B	R-L
SVM	3336	3336	3336	3336	3336	3336	6672	6672	6672
Time selection	1008	930	1350	1068	1278	1008	2088	2016	2388
Channel selection	1946	2398	1633	2016	2155	1911	2016	2259	2085
Direct selection	179	227	185	266	218	179	161	217	173



(a) Subject 1

(b) Subject 2

Fig. 5. Results of direct selection of FB-RL by both Hb for two subjects. Gray solid, gray dashed, black solid, and black dashed lines indicate average signals during the task for front, back, left, and right directions, respectively. Gray zone indicates selected position.

accuracy was in the order of all features SVM < time selection SVM < channel selection SVM < direct selection SVM. fNIRS is often used to examine mainly spatial localization, such as mapping the amplitude of each channel to the cerebral cortex. However, our results suggest that force directional information was localized not only in the channel but also in the time dimension because the classification accuracy of direct selection SVM was the highest.

Fig. 5 shows that selected feature position of direct selection of FB-RL by both Hb for two subjects. Selected channels that were not found tend to match in both subjects. Time was selected near 4, 12, and 17 [s] for both subjects; 4 [s] is the time it takes for fNIRS signal rises in general and represents the peak position of the signal. 12 [s] is the time the task ends. 17 [s] may represent the trend.

V. CONCLUSION

Applying feature selection by using the SLR, we suggested that information about force direction in fNIRS was localized in both time and channel dimensions. The peak time of the signal, when the task ends, and a few seconds after the task ends, were particularly well selected. On the other hand, selected channels that were not found tend to match between the subjects. The reason could be that the measurement data sets contain displacement of channel position that cannot be controlled for each subject and channel.

If features are selected by using SLR from OxyHb and DeoxyHb, the classification accuracy became high with more than 95 [%] for each classifier. However, this accuracy was inappropriate to evaluate the performance of online classification because training was included on the test data when the feature position was selected by SLR. If SLR training to select feature position was performed in only training data to evaluate the performance of online classification, the classification accuracy was almost unchanged with all features SVM. If training and test data is generated from the same distribution, the optimal feature position could be estimated in the only training data. However, in fact, data distribution was changed due to a shift of channel position and change in the signal to noise ratio because data was measured over the course of five days. Therefore, we need to investigate the method to allow for or correct a change for each day.

VI. ACKNOWLEDGMENTS

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