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Temporal representation of arm force direction using fNIRS signals

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***Abstract*— We investigated the possibility of creating a temporal representation of brain activity from fNIRS signals. In an experiment, subjects performed isometric arm movements in four directions, and fNIRS signals were measured over the primary motor area in the left hemisphere of their brain. We estimated the direction of the arm force from the fNIRS signals by using two classifiers: sparse linear regression (SLR) and support vector machine(SVM). Classification accuracy was approximately 70% with SLR. The temporal distribution of the features selected with SLR was the same as those selected with SVM. The results indicated that the fNIRS signals possibly included information about arm force direction in 4–6 [s] after stimulus onset and offset.**

I. INTRODUCTION

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

Noninvasive neuroimaging techniques include electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and functional near infrared spectroscopy (fNIRS). fNIRS measures the oxygenated hemoglobin (Oxyhb) and deoxygenated hemoglobin (Deoxyhb) concentrations in the brain surface blood flows, which may be associated with brain activity [3]. 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 activity when the subject is moving.

Sparse logistic regression (SLR) has been getting much attention in various fields. It has been applied to image discrimination from fMRI signals [4] and estimation of finger pinch force from fNIRS signals [5]. SLR is a Bayesian extension of logistic regression, and simultaneously performs feature selection and training of the model parameters. In an experiment measuring brain activity, the obtained features were too numerous compared with the number of samples. Therefore, feature selection is necessary to prevent overfitting. This feature selection can be done simultaneously with training by using SLR that enables to estimate brain information to be interpreted from selected features.

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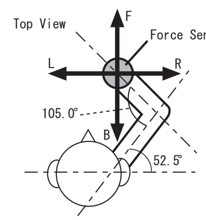

Fig. 1. Arm angle

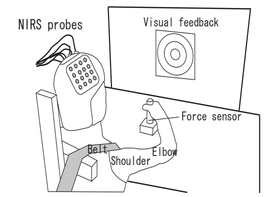

Fig. 2. Experimental setup

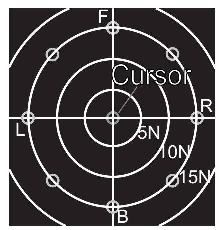

Fig. 3. Visual force feedback

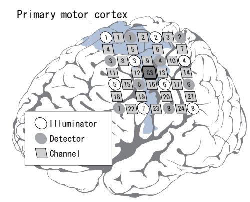

Fig. 4. Probe and channel positions on left hemisphere

A previous study showed that it might be possible to estimate the arm force direction from fNIRS signals [6]. Another study showed that a spatial representation of information about body movement may be contained in fNIRS signals through channel selection using support vector machine (SVM) [7]. Spatial representation was sufficiently elucidated by result of it. Whereas, temporal representation was not. The number of combinations became too large when trying to create a temporal representation by using a time window search with SVM. Thus, this method is not practical because of requirement of much computational cost and time.

In this study, we created a temporal representation by using SLR. This method has less computational cost than a time window search with SVM. In particular, we estimated the direction of arm force with SLR from fNIRS signals that were measured during isometric arm movements in four directions, in the same way as with the previous studies. We were able to create a temporal representation of the force direction derived from fNIRS signals by using the temporal distribution of selected features.

II. EXPERIMENTAL METHODS

This study was approved by the ethics board of the Nagaoka University of Technology. Eleven healthy men (S1 to S11) assented to and participated in the experiment. S2 was left-handed, and the others were right-handed. All performed the task with their right hand.

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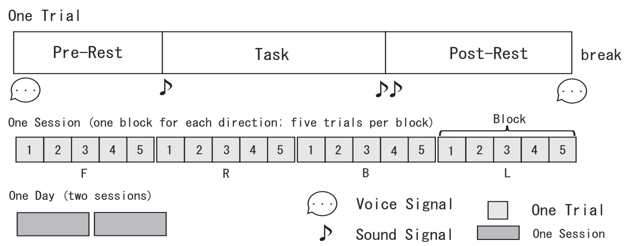


Fig. 5. Experimental task procedure

The task involved a right-hand isometric muscle contraction at 15 [N] with the force directed in one of four directions: forward (F), right (R), backward (B), left (L) (Fig. 1).

The subject sat in front of a display with his body strapped to the chair using a belt as shown in Fig. 2. 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 when the angle of the right arm was 105° as shown in Fig. 1.

Fig. 3 shows the visual feedback displayed on the screen. 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 14 to 16 [N], and red when more than 16 [N]. The feedback view was placed at the center of the subject's visual field to avoid eye movement. The distance from the subject's eyes to the display was set to 95 [cm]. The cursor diameter was 1.5 [cm]. The 15 [N] circle diameter was 25 [cm].

Since the contralateral hemisphere of arm movement is activated, the fNIRS signals were measured over the left hemisphere because the subjects performed the task with their right arm. The fNIRS probes and channels were located around C3 of the international 10-20 system as shown in Fig. 4. The fNIRS signals were measured for a sampling period of 130 [ms]. In the initial experiment, 5544 data points were measured for each trial, and 4824 points were measured in the additional experiment.

Six subjects (S1 to S6) participated in the initial experiment, and the other five (S7 to S11) participated in an additional experiment, which differed from the initial one in terms of the timing. The subjects performed the experiment over the course of five days.

Fig. 5 shows the experimental procedure. In the initial experiment, a session consisted of four blocks corresponding to the four directions. Each block consisted of five trials. A trial consisted of an 8-[s] pre-rest, a 12-[s] task, and a 10-[s] post-rest. A dataset for 50 trials was obtained for each direction. To prevent inter-trial interference, a 30–60 [s] rest was given between trials, and the next measurement started after stabilization of the fNIRS signals. In the additional experiment, a trial consisted of an 8-[s] pre-rest, an 8-[s] task, and a 10-[s] post-rest. The compositions of the blocks and sessions were the same as in the initial experiment.

TABLE I
NUMBER OF USABLE TRIALS

Subject	F	B	R	L
1	34	48	38	23
2	33	28	25	29
3	41	44	19	33
4	50	50	50	50
5	47	50	47	50
6	50	50	50	50
7	48	44	48	46
8	50	32	19	33
9	50	50	50	49
10	50	50	50	50
11	49	47	49	38

III. ANALYSIS

A. Pre-processing

We set the start time (0 [s]) with the time when the force reached 3 [N] and set the end time when it fell below 3 [N] in order 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 start to end of movement. The multiple comparison was performed using the Tukey-Kramer method with the significance level set to 1%. TABLE I shows the number of trials used in the analysis.

The mean value during pre-rest was used as a baseline, which was subtracted from the original signal. To remove noise, a fourth-order Butterworth low-pass filter (0.5 [Hz]) was used.

B. Classification

SLR and SVM were used to estimate arm force direction. Estimations for three groups were performed: FB-RL which classify FBRL data into FB class and RL class, F-B which classify FB data into F class and B class, and R-L which classify RL data into R class and L class. This method required fewest classifier when classify four direction data into four class.

1) Sparse Linear Regression: In the SLR model, the linear discriminant function separating two classes was represented by the weighted sum of each feature value:

$$f(\mathbf{x};\boldsymbol{\theta}) = \sum_{d=1}^{D} x_d \theta_d, \quad (1)$$

where $\mathbf{x} = (x_1, ..., x_D)^t$ is the input feature vector and $\boldsymbol{\theta} = (\theta_1, ..., \theta_D)^t$ is the weight vector. The possibility that the input vector belongs to class C is given by

$$p = \frac{1}{1 + exp(-f(\mathbf{x};\boldsymbol{\theta}))} \equiv P(C|\mathbf{x}). \quad (2)$$

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

$$P(y_1, ..., y_N|\mathbf{x}_1, ..., \mathbf{x}_N;\boldsymbol{\theta}) = \prod_{n=1}^{N} p_n^{y_n}(1-p)^{1-y_n}, \quad (3)$$

where y_n is a variable such that $y = 0$ if the sample belongs to class1 and $y = 1$ otherwise. The $\boldsymbol{\theta}$ that maximizes the likelihood is calculated in two steps.

$\boldsymbol{\theta} step$:

$$E(\boldsymbol{\theta}) = \sum_{n=1}^{N} \left\{ y_n \boldsymbol{\theta}^t x_n - log(exp(\boldsymbol{\theta}^t x_n)) \right\} - \frac{1}{2} \boldsymbol{\theta}^t \bar{A} \boldsymbol{\theta} \quad (4)$$

$\alpha step$:

$$\bar{\alpha_d} = \frac{1 - \bar{\alpha}_d s_d^2}{\bar{\theta_d}^2} \quad (5)$$

The α is referred to as the relevance parameter. It controls the possible range of the corresponding weight parameter. Most of the estimated α_d diverges to infinity, and the corresponding weights become zero through iteration of the two steps above. As a result, most of the features eliminated, and we obtained a sparse model.

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

$$f(\mathbf{x}) = \mathrm{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i^* K(\mathbf{x}, \mathbf{x}_i) + b^* \right), \quad (6)$$

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.

$$\begin{aligned} \text{max.} \quad & W(\boldsymbol{\alpha}) = \sum_{i=1}^{\ell} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\ell} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ \text{sub. to} \quad & 0 \le \alpha_i \le C, \ i = 1, ..., \ell, \quad (7) \\ & \sum_{i=1}^{\ell} \alpha_i y_i = 0 \end{aligned}$$

C is an appropriate positive penalty parameter. The threshold level b^* is given by

$$b^* = \frac{1}{|I|} \sum_{i \in I} \left(y_i - \sum_{j=1}^{\ell} y_j \alpha_j^* K(\mathbf{x}_i, \mathbf{x}_j) \right). \quad (8)$$

Here, I is the set of support vectors. Sequential minimal optimization (SMO) was used to solve this problem. The linear kernel function was

$$K(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{x}_1^T \mathbf{x}_2. \quad (9)$$

C. Data analysis and evaluation

The input dataset excluded trials in which the force value was significantly different from the average. Additionally, the measurement time for each trial data point was set from the start to 6 [s] after finishing the movement, resulting in 18-[s] long (14-[s] long in additional experiment). All models were evaluated using five-fold cross validation. All trials were sorted with random order and separated into five blocks. Four blocks were used for learning to obtain the parameters. Evaluation was performed using another block and the obtained parameters. The learning and evaluation were performed for all combinations. It was repeated eight times, while blocks were rearranged in each trial. The classification accuracy was the average for 40 times evaluations.

TABLE II
CLASSIFICATION ACCURACY WITH SLR

Subject	FB-RL [%]	F-B [%]	R-L [%]
1	78.76	64.52	78.99
2	72.39	74.24	75.11
3	79.24	64.65	81.61
4	79.13	66.69	66.25
5	68.72	64.51	69.40
6	72.25	72.56	66.88
7	71.28	64.32	67.70
8	63.06	61.86	73.79
9	69.20	67.40	66.21
10	74.13	68.38	70.38
11	63.25	60.14	59.25
Average	71.95	66.30	70.51

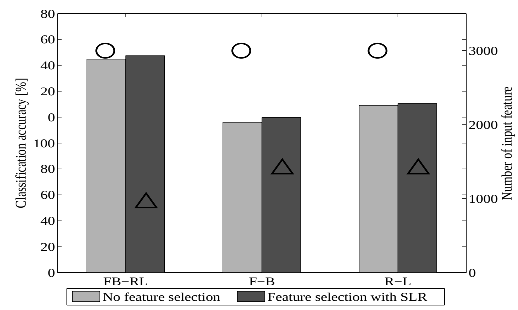


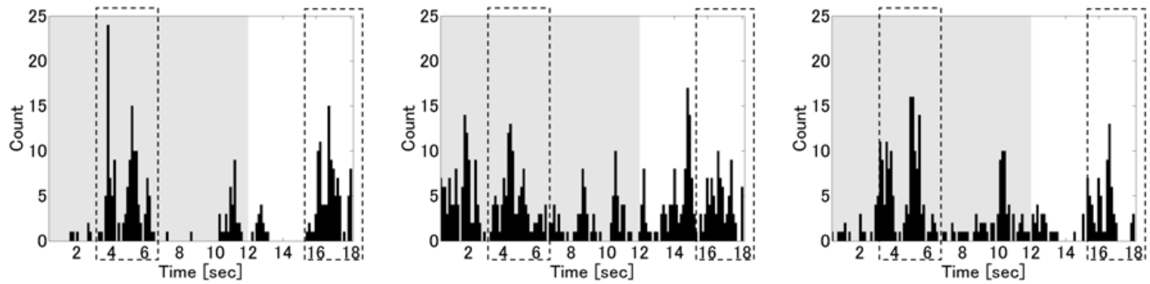
Fig. 6. Classification accuracy with SVM. Bar graphs represented classification accuracy. The circles represented the number of input feature. The triangle represented the number of input feature with feature selection.

IV. RESULTS

TABLE II shows the classification accuracy with SLR. The classification accuracy was approximately 72% for FB-RL, 66% for F-B, and 70% for R-L at average of all subjects.

Fig. 6 shows the classification accuracy and number of input features with SVM, without and with feature selection with SLR. Bar graph represented classification accuracy and The circles and triangles represented the number of input feature. Feature selection with SLR selected more than four times out of 40 estimations were used. As a result, SVMs with and without feature selection were similar in the classification accuracy. However, the number of input features decreased to approximately half when feature selection was used. Since feature selection with SLR reduced the number of input features, these results suggested that the features selected with SLR are thought to have included information about the force direction.

Fig. 7 shows the temporal distribution of the number of features selected with SLR. The horizontal axis represents time, and the vertical axis represents the number. Count represents the number of times where the channels were selected in 40 times of learning. In FB-RL and R-L classification, the features that appeared at 4 to 6 after the start and end times were frequently selected, indicating that the features selected with SLR probably reflected brain activity and that information was comprised in this term. The difference of fNIRS signals appeared at wide time but all of them not necessarily included information. In our previous study, the



(a) FB-RL classification (b) F-B classification (c) R-L classification

Fig. 7. Temporal distribution of number of selected features

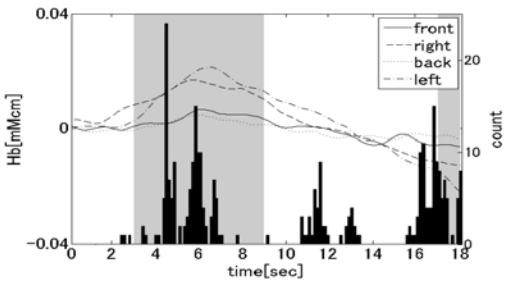


Fig. 8. Result of temporal feature selection using SVM

difference of fNIRS signals appeared at nearly all channels while the number of channels which available to estimation was approximately 10 out of 24 channels.

In F-B classification, the features that appeared soon after the start were frequently selected. These features were thought to reflected motion planning process.

To test temporal local existence, a time window search was performed using SVM, and the results were compared with those with SLR. Two windows with variable widths and start times were used in the time window search. The widths were 1–17 [s] and slid in steps of each 1 [s] between 0–(18-width) [s]. Fig. **??** shows the results of the time window search along with example plots of fNIRS signals. The horizontal axis represented time, the left vertical axis represented variation in the fNIRS signal, and the right vertical axis represented the number of selected features. The histograms represented the number selected with SLR. The shaded areas showed the results of the time window search with SVM. The results were a little different from the temporal distribution of features selected with SLR, but similar terms were selected: those that appeared at four to six seconds later of the start and end times. These terms thus had a high probability of including information about the arm force direction because similar terms were selected with SVM and SLR.

V. CONCLUSION

We investigated the temporal representation of arm force direction through the estimation of the force direction from fNIRS signals using SLR. Accuracy was approximately 72% for FB-RL classification, 66% for F-B classification, and 70% for R-L classification. SVMs with and without feature selection were similar in the classification accuracy. However, the number of input features became approximately half by feature selection. Thus, features selected with SLR included brain information concerning arm movements because the number of input feature decreased but classification accuracy was same as before. The selected features were similar with those using a time window search with SVM. Thus, those features probably included information about the arm force direction.

VI. ACKNOWLEDGMENTS

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