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Estimation of the direction of arm force by using NIRS signals

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Abstract— **In this study, we tried to discriminate the direction of arm force from hemoglobin concentration changes measured by near-infrared spectroscopy (NIRS). A self-organizing map (SOM) was used to classify the force direction information obtained from the NIRS signals. In a human subject experiment, the subjects were required to perform isometric arm movements in four directions. We investigated the feature quantities extracted from the time series data of the NIRS signals during the movement task. The feature vectors were used as the input vectors to the SOM. We tried to estimate the arm force direction by using a simple method based on the clusters given by the SOM. The results confirm that the direction of force is discriminable from the NIRS signal. In spite of the simple classification approach, the discrimination test yielded an average discrimination rate of 87.5 % for two directions. The experiment results suggest that NIRS signal must contain information related to the force directions.**

I. INTRODUCTION

Brain computer interface (BCI) able to interpret biological signals from the human brain have recently been developed. BCI users are required to control brain activity that can be measured by electro encephalic gram (EEG) or from blood oxygenation level dependent (BOLD) signals. The user controls his or her brain activity by imagining or by recalling something; that is, brain activity might be controlled without the user activating their muscles. Because of the possibility that a robot can be controlled without muscle activation, BCI has recently attracted a lot of attention as a potential communication tool for such individuals as amyotrophic lateral sclerosis (ALS) patients who cannot communicate with others easily.

Many implementations using EEG have been studied [1]-[3]. On the other hand, near infrared spectroscopy (NIRS) has recently drawn attention as a brain activity measurement technique. Some researchers have studied the relation between muscle activities and brain activities detected by NIRS [4]. Moreover, a BCI based on NIRS has also been reported [5][6]. Sitaram [7] discriminated NIRS signals during an imagery finger-tapping task using both hands and then estimated for which hand the movement was imaged. In our previous study [8], we devised a method for classifying the NIRS signals into right- and left-hand movements and imagery. The relationship between NIRS signals and the magnitude of force has also been investigated [9]-[11].

In this study, we considered the possibility of discriminating the direction of arm force based on hemoglobin density by using NIRS and devised a method for estimating the direction to apply the arm force. We performed experiments with subjects and distinguished NIRS signals during isometric arm movements in four directions. We analyze the time series data of NIRS signals during the movement task and extracted feature quantities. After that, we used a self-organizing map (SOM) to classify the NIRS signals during the isometric movement task. The feature vectors extracted from NIRS signal were used as the input vectors to the SOM. We discriminated the directions of arm force by using a simple method based on the clusters given by the SOM.

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II. NIRS MEASUREMENT DURING ISOMETRIC MOVEMENT TASK

Five right-handed subjects (JA, KN, KNa, MM, YM) and one left-handed subject (TI) participated in the experiments. All subjects performed a given task with their right arm. Informed consent was gotten from all subjects. The experimental setup is shown in Fig. 1. Subjects sat facing a display

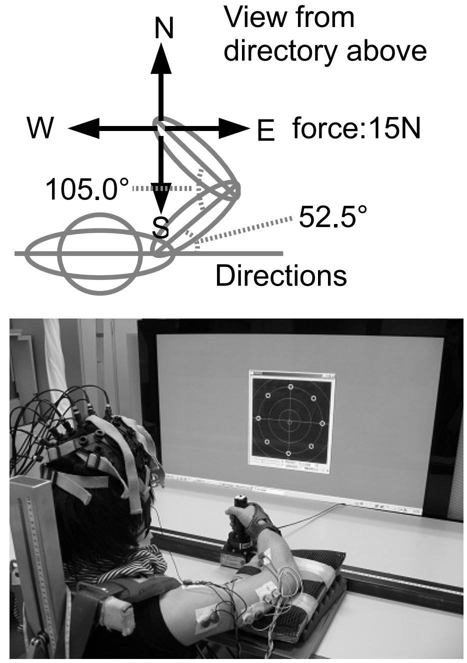

Fig. 1. Experimental environment

in chairs adjusted to lift their arms to shoulder level, and their right wrists were supported by a brace. Their left arms rested naturally by their side. Subjects performed isometric movements with four directions by using their right arm. Each force direction is shown in the upper figure of Fig. 1. The direction of the display was depicted as N. The

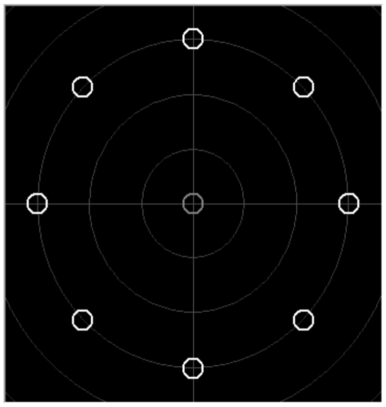

Fig. 2. Display feedback

Fig. 3. Probe position on left hemisphere

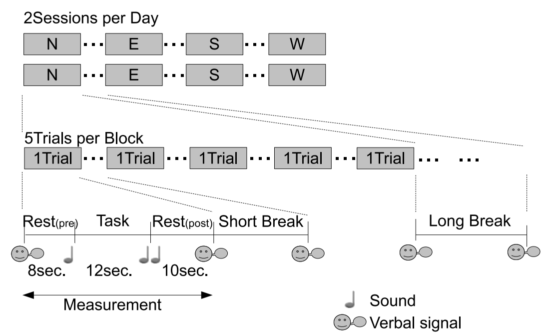

Fig. 4. Experimental procedure during a day

directions to the right, left and subject side were depicted as E, W, and S, respectively. A force sensor (Niita Corp.) was clasped by the subjects. The angles of subject's shoulder and elbow were as shown in the lower figure of Fig. 1.

The subject performed the force generation task of applying 15 N in each direction indicated in the upper figure of Fig. 1. The force amplitude was shown on the display in Fig. 2 as feedback to the subjects. A cursor corresponding to the force vector projected on a horizontal plane was indicated on the display. Concentric circles represented the force amplitude, and circles corresponding to 5[N], 10[N], 15[N] were arranged in increasing order of radius. If the generated force was less than 14[N], the cursor was colored blue. Similarly, if the force was greater than 16[N], the cursor was colored red. Otherwise, the cursor was colored yellow. The distance between subject and display was about 95[cm] because subjects could look at the whole display. The cursor size was 15[mm] in height and width. The radius of the concentric circle for 15[N] was 25[cm].

A fiber cap for the NIRS measurements was installed on the left hemisphere of the subjects' heads. Surface electrodes for the EMG measurements were attached to their right arms. In the experiments, hemoglobin signals from the hemispheres of the brain, EMGs on the right arm, and force were measured at the same time. Oxy-Hb and deoxy-Hb were measured by using NIRStation (OMM-3000/8, Shimadzu Corporation). Total-Hb was defined as the sum of oxy-Hb and deoxy-Hb. Twenty-four channels on the hemisphere of the brain were selected to be measured around C3 on the basis of internationally standardized 10-20 system shown in Fig. 3.

Each subject alternately rested (REST(pre): 0[s]$\sim$8[s], REST(past): 20[s]$\sim$30[s]) and executed the task (8[s]$\sim$20[s]). A beep sounded to signal the beginning and end of a task. The following instructions were given to the subject: "breathe with a constant rhythm while executing the task." The experiments were performed over the course of five days. The schedule for one day is shown in Fig. 4. One session consisted of 4 blocks with 5 trials for each direction, namely, 20 trials in total. Two sessions (40 trials) were given each day. Therefore, for each subject, we obtained data sets of 50 trials for each direction. A total of 200 trials were obtained.

III. Analysis

A. Processing of measured data

To remove the influence of breath and heart rate, a fourth-order Butterworth lowpass filter of 0.5 Hz was used. Afterwards, the mean value of Rest(pre) of each trial was assumed to be the baseline, and it was subtracted from the original signal.

B. Self-organizing maps

We constructed a two-dimensional map for feature extraction based on Kohonen's self-organizing map. The map had two-dimensional connections with a 20$\times$20 matrix structure as shown in Fig. 5. The number of neurons was 400. A feature map was constructed for each measured channel of NIRS.

The update formula for a neuron with a weight vector was based on batch learning. For the batch learning, the weight corrections were summed and globally corrected for all neurons after each epoch. We used a torus SOM, which has a torus structure for connecting neurons .

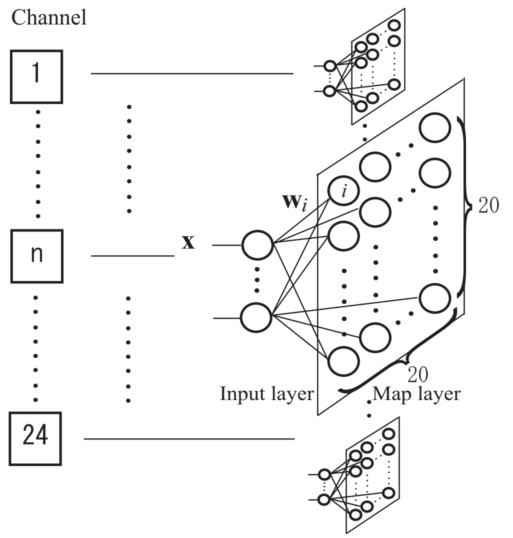

Fig. 5. Self organizing maps with respect to each channel

The learning procedure of SOM is as follows. The winner neuron was selected for the minimum of the Euclidean distances from the input vector by using a winner-takes-all function:

$$i^* = \arg\min_i \|\mathbf{x} - \mathbf{w}_i\|, \quad (1)$$

where $i = 1, 2, \ldots, 400$ is the index of the neuron, i^* shows the winner neuron, **x** is the input vector, and $\mathbf{w}_i$ is the weight of the i-th neuron. The adjustment to the weight in the learning phase is represented by

$$\Delta\mathbf{w}_i = \frac{\eta}{M}\Lambda\left(i, i^*, \sigma_\Lambda(t)\right)\left(\mathbf{x} - \mathbf{w}_i\right), \quad (2)$$

where $\mathbf{r}_i$ is the lattice coordinate of the neuron, t is the learning step, t_{max} is the iteration number of the learning epoch, and M is the number of input vectors. The neighborhood function $\Lambda\left(i, i^*, \sigma_\Lambda(t)\right)$ and the monotone decreasing function σ_Λ are defined as

$$\Lambda\left(i, i^*, \sigma_\Lambda(t)\right) = \exp\left(-\frac{|\mathbf{r}_i - \mathbf{r}_{i^*}|^2}{2\sigma_\Lambda(t)^2}\right), \quad (3)$$

and

$$\sigma_\Lambda = \sigma_{\Lambda_0}\exp\left(-2\sigma_{\Lambda_0}\frac{t}{t_{max}}\right). \quad (4)$$

The training parameters of the SOM are listed in Table 1.

TABLE I
TRAINING PARAMETERS OF SOM

Map size	20×20
Number of iterative learnings t_{max}	20000
Coefficient for weight renewal η	0.05
Coefficient for reduction function$\sigma_{\Lambda 0}$	10
Initial weight	uniform random numbers

By using the listed parameters, we confirmed that the weights well-converged within 20,000 epochs.

C. Feature vectors for learning

The feature vectors of the SOM corresponding to each channel were extracted from the time series of NIRS data. The time interval for the feature set was determined as 8[s]∼30[s]. The measured signals were converted into time-series signals by resampling at 1 [Hz]. This resampled data was an average of 14 points (= 1/0.07) for 1 [s]. Namely, the feature vectors $\mathbf{x_i} = (x_{i,1}, \ldots, x_{i,n}, \ldots, x_{1,21})$, where $i = 1, 2, 3, 4$ is the index of learning set and $n = 1, 2, \ldots, 21$ is the index of the n-th element of the feature vectors, had 21 dimensions.

The feature vectors of 50 trials for each direction were divided into sets of 10 consecutive trials. Four sets (40 trials) were used for training, and one set was used for the test. The average feature vectors were calculated from 10 trials from each training set. The training set of the SOM for each channel for each direction is represented by

$$\mathbf{X} = (\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_3}, \mathbf{x_4})^T \quad (5)$$

$$\begin{aligned} \mathbf{x_1} &= (x_{1,1}, x_{1,2}, \ldots, x_{1,21}) \\ \mathbf{x_2} &= (x_{2,1}, x_{2,2}, \ldots, x_{2,21}) \\ \mathbf{x_3} &= (x_{3,1}, x_{3,2}, \ldots, x_{3,21}) \\ \mathbf{x_4} &= (x_{4,1}, x_{4,2}, \ldots, x_{4,21}). \end{aligned} \quad (6)$$

D. Method for discriminating the direction of arm force

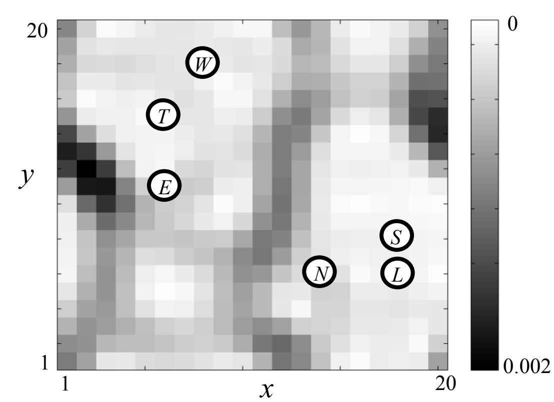

Fig. 6. Gray scale image for SOM, (Subject YM, Ch-1), (x and y indicate neuron indexes. T, L, N, E, W and S show winner neurons corresponding to the respective average data of transversal, longitudinal, north, east, west and south.)

Figure 6 shows an example of gray-scale SOM image of after training. Small boxes mean neurons arranged in a 20×20 plane. The figure shows the root-mean-square distance from neighbor neurons. A neuron which has the minimum mean error of weight vector between itself and neighbor neurons is depicted as white. A neuron which has the maximum mean error is depicted as black. Characters T, L, N, E, W and S show winner neurons when the average training data was used for each direction. Note that, "transversal" means set of east and west and "longitudinal" means set of north and south.

From this result, we can confirm that there are two clusters corresponding to the transversal and longitudinal directions. Hence, we tried to classify the test data by using the feature map information. Denoting the location of the winner neuron on the 20×20 plane for the input test data as (x, y) and the location of the winner neurons corresponding to the transversal and longitudinal data as (x_{win-T}, y_{win-T}) and (x_{win-L}, y_{win-L}), respectively, we calculated the Manhattan distance between (x_{win-T}, y_{win-T}) or (x_{win-L}, y_{win-L}) and (x, y).

$$d_{direction} = |x - x_{win}| + |y - y_{win}| \tag{7}$$

We estimated the arm force directions as follows: if $d_{Longitudinal} < d_{Transversal}$, the longitudinal direction was assumed, and if $d_{Transversal} < d_{Longitudinal}$, the transversal direction was assumed. This estimate was made for each channel, and conclusive discrimination was determined from majority operation of the selected channels. The channels were selected by identifying the channels most related to discrimination. We used 5-fold cross validation to evaluate the discrimination rate.

IV. Results

Table 2 shows the mean discrimination rate for each subject, and Table 3 shows the average. By using oxy-Hb and total-Hb, we obtained discrimination rates from 77% to 95%. The average of all subjects was 87.5% for total-Hb. These results were obtained from majority operation of about 10 channels most related to discrimination. If all 24 channels were used, the discrimination rate was 82.8% for total-Hb.

TABLE II

Average discrimination rate (two directions)

	total-Hb	oxy-Hb	deoxy-Hb
Subject JA	89.0%	89.0%	78.0%
Subject KN	84.5%	82.5%	71.5%
Subject KNa	74.0%	77.5%	65.0%
Subject MM	93.5%	91.0%	75.0%
Subject TI	89.0%	88.0%	69.0%
Subject YM	95.0%	84.0%	81.0%

TABLE III

Average discrimination rate of all subjects (two directions)

	total-Hb	oxy-Hb	deoxy-Hb
average	87.5%	87.0%	73.3%

Finally, we tried to classify the four directions. The results are shown in Tables 4 and 5. The average of all subjects was 55.5% for oxy-Hb. Discriminating one of four directions was much more difficult than discriminating one of two directions.

V. Conclusions

We developed a method to discriminate the direction of arm force from hemoglobin concentration changes measured by NIRS. A SOM was used to classify NIRS signals during isometric arm movements in four directions. We estimated the direction of arm force by using a simple method based on the clustering performance of SOM. We confirmed that the direction of force is discriminable from NIRS signals in a human subject experiment. Especially in the discrimination test for longitudinal and transverse directions, the average discrimination rate was 87.5 %. The experiment results suggest that NIRS signals must contain information related to the force directions.

TABLE IV

Average discrimination rate (four directions)

	total-Hb	oxy-Hb	deoxy-Hb
Subject JA	62.0%	59.0%	47.5%
Subject KN	48.5%	49.0%	39.5%
Subject KNa	50.5%	47.0%	36.0%
Subject MM	56.0%	59.5%	41.0%
Subject TI	58.0%	59.0%	38.5%
Subject YM	57.0%	59.5%	41.5%

TABLE V

Average discrimination rate of all subjects (four directions)

	total-Hb	oxy-Hb	deoxy-Hb
average	55.3%	55.5%	40.7%

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