PAPER

Construction of an Electroencephalogram-Based Brain-Computer Interface Using an Artificial Neural Network

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SUMMARY A brain-computer interface using an electroencephalogram as input into an artificial neural network is investigated as a potentially general control system applicable to all subjects and time frames. Using the intent and imagination of bending the left or right elbow, the left and right desired movements are successfully distinguished using event-related desynchronization resolved by fast Fourier transformation of the electroencephalogram and analysis of the power spectrum using the artificial neural network. The influence of age was identified and eliminated through the use of a frequency distribution in the α band, and the recognition rate was further improved by confirmation based on forced excitement of the β band in the case of an error. The proposed system was effectively trained for general use by using the combined data of a cross-section of subjects.
key words: *electroencephalogram, event-related desynchronization, artificial neural network, brain-computer interface, fast Fourier transform*

1. Introduction

The number of people who have lost movement or language function due to traffic accidents or neuromuscular disease in Japan has reached 100,000 [1], necessitating large numbers of care assistants to support severely disabled patients who have almost no voluntary control of body movements. This is a global trend in developed countries, where an increasing number of care assistants are allocated to the rapidly increasing elderly population. A wide range of electronic device have been developed specifically to reduce the care workload and the number of care assistants needed [2].

Functional electrical stimulation (FES) is one technique that has been studied for the reconstruction of lost movement functions [3]. Patients with spinal injuries are unable to perform movements because the brain signal intended for movement of their extremities is not transmitted to the peripheral nerves. If these control commands could be correctly input into an FES system, electric stimulation from the system may be able to activate the peripheral nerve and move the extremity. Transmission of these intents to devices is important but time-consuming work for severely paralyzed patients.

The success of an FES system is strongly dependent on technological advances for both input and output. Specifically, the method of input should reflect the intent of the patient so that the output of electrical stimulus correctly activates the nerve of interest. Current systems developed to assist the physically disabled to interact with computers include voice [4], eye-movement [5] and respiratory [6] based interfaces. However, using the electroencephalogram (EEG) of these patients as a computer interface has the potential to easily convey their intents to peripheral nerves. The clinical utilization of such systems for the aid of patients and care assistants is investigated in this study.

A computer interface based on EEG, namely a Brain Computer Interface (BCI), is a communication system that categorizes different EEG patterns and produces a control signal according to the categorized results [7]–[14]. For example, EEG patterns generated in the sensorimotor cortex have been detected for the preparation and execution of movement [9], [10] or for imagining movement [8]. Sinistral and dextral body movements are distinguished by the well-known differences in EEG patterns in the preparatory phase before a movement [9], [10]: in the pre-movement period, event-related desynchronization (ERD) reveals distinct contralateral features [11], whereas the EEG desynchronization pattern during movement is bilateral. The BCI system is suitable for disabled patients to control input devices such as a cursor on a screen, allowing for choice selection and even written communication by expressing the Morse code, i.e. the sinistral and dextral movements correspond to the dot and dash.

In the present study, the EEG generated when the subject imagines the bending of the left or right elbow is investigated for potential application to an EEG-based BCI. The EEG is processed by fast Fourier transformation (FFT), and a power spectrum is calculated. Based on the values of the power spectrum, the sinistral or dextral movements are distinguished by inference using an artificial neural network (ANN) operated off-line. This ANN has been successfully used with EEG

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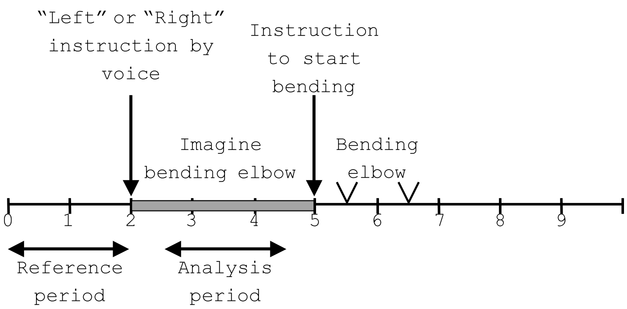

Fig. 1 Timing of events during EEG collection (time in seconds).

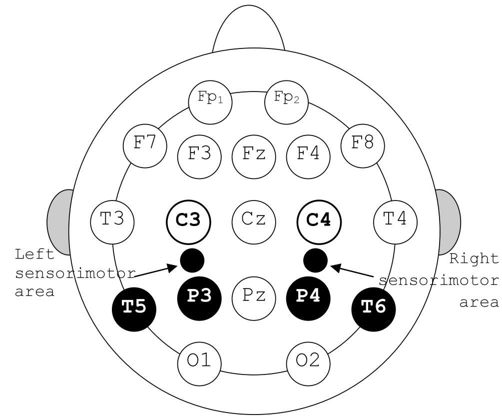

Fig. 2 Electrode positions viewed from the top of the head.

data in previous studies to quantitatively evaluate the severity of cerebral disease and the degree of aphasia in patients suffering speech loss [15]. The present authors have also investigated the use of an ANN model to predict HDS-R scores of Alzheimer dementia patients [16].

A similar study was performed by Pfurtscheller et al. [13], who used EEG data for the sensorimotor cortex with a learning vector quantization (LVQ) neural network system. They were able to correctly distinguish about 93% of left and right movement-related EEG patterns in some subjects. However, the LVQ system requires training and adjustment for each individual subject because of differences in EEG patterns between individuals. This training and adjustment process is difficult and time-consuming, particularly when considering possible significant changes in EEG patterns during the first EEG sessions due to involvement of the mood of the subject. In the present study, a more general model is developed, in which EEG patterns can be categorized at different times and for different subjects without remodeling.

2. Methods

2.1 EEG Recording

The subjects were eight healthy males: A, B, C, D, E, F, G, and H (ages 25, 23, 34, 40, 56, 60, 72 and 72, respectively); three healthy females: I, J, and K (aged 23, 20 and 20); and three patients with cervical spine injuries: L, M, and N (aged 17, 25 and 46). The EEG was obtained according to the timing shown in Fig. 1. This process is almost the same as used by Pfurtscheller et al. [13]. After the EEG electrodes were attached, the subjects were instructed to lie in a relaxed condition on the bed in a darkened and shielded room and to close their eyes. After hearing the words "left" or "right" spoken by an instructor, the subjects were asked to imagine that they were bending either their left or right elbow for 3 seconds. After hearing an instruction to start bending the elbow on a particular side, they did as instructed. The EEG collected during the 2 seconds before the subjects imagined that they were moving an elbow was used as a reference. The EEG used for the imagined movement started at 2.5 seconds and ended at 4.5 seconds during the start of the 3-second imagining period. Electrodes were placed according to the international 10–20 system as illustrated in Fig. 2. Linked bimastoid electrodes were used as the reference. The EEG was recorded from the left and right sensorimotor areas, T5, T6, P3 and P4, on a total of 6 channels.

2.2 Pre-Treatment of Data

For all subjects, EEG data were collected for 60 imagined left or right movements (30 pairs), from which 45 artifact-free EEG sequences were selected. EEG data for the 2-second period before and during the imagined movement were sampled at 100 Hz, and 200 data points were used for FFT, which was performed using a Hanning window and 2^8 (256) data (the remaining 56 points were complimented by zero padding). The power spectrum was obtained at intervals of 0.390625 (= 100/256) Hz. The EEG data were analyzed every hertz, and two successive power spectra (= 0.78125 Hz), which is close to this interval, were used for calculation of the ANN. The ERD is an event-related electric potential that was observed as a decrease in the μ wave (7–13 Hz) or β band (14–30 Hz) in the pre-movement period [9]. Since eye movements and electromyography may significantly affect the ranges of 1–6 Hz and > 25 Hz, the range 7–25 Hz was initially selected as a rough candidate for input into the ANN.

The original power spectrum data were binarized as follows before inference by the ANN. Let R be the power spectrum value during the 3-second period of imagined movement, let P be the standard power value during the 2 second prior to the imagined movement (Fig. 1), and let subscripts r and l represent the right and left hemisphere. The data were set to 1 when the ratio of R to P in the right hemisphere was larger than that of the left ($R_r/P_r > R_l/P_l$), and to 0 for the opposite case ($R_r/P_r < R_l/P_l$). This procedure was applied to 3 pairs of channels (i.e., left-right sensorimotor ar-

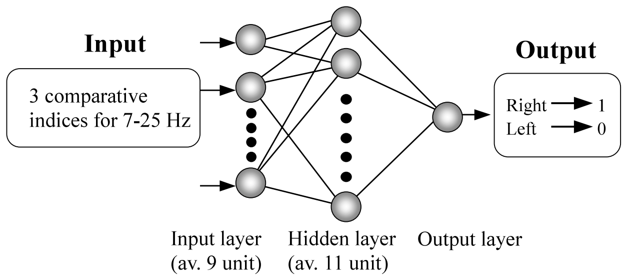

Fig. 3 ANN structure.

eas, T5–T6, and P3–P4), and three comparative indices were determined for each frequency band.

2.3 ANN System and Evaluation Method

(1) ANN system
A three-layered ANN with input, hidden and output layers was employed [15], [16] (Fig. 3). The teaching signal of the constructed ANN was set to 1 or 0 for the judgment of right or left movement, respectively. For the individual subject, the number of data for learning was set to 30, and 15 data were set for evaluation. For the entire data set, input values and teaching values were normalized between 0.1 and 0.9.

As a performance index of the estimation model, the mean value of the square error, given by the following equations, was used as a performance index J.

$$J_1 = \frac{1}{n_1}\sum_{i=1}^{n_1}(O_i - T_i)^2 \tag{1}$$

$$J_2 = \frac{1}{n_2}\sum_{i=n_1+1}^{n_1+n_2}(O_i - T_i)^2 \tag{2}$$

$$J = \frac{J_1 + J_2}{2} \tag{3}$$

where J_1 and J_2 are the mean square errors for learning data and evaluation data, and n_1 and n_2 are the total number of data for learning and evaluation. The back-propagation algorithm [17] was used for learning, with random initial connection weights for the ANN models.

The constructed model may not be suitable if some of the input variables are unnecessary. Therefore, the optimized input variables were selected by the parameter increasing method (PIM) [18]. The PIM identifies an ANN model by step-wise incrementation of the number of input variables. ANN modeling by PIM was performed with every combination of input variables in each step. The combination of input variables giving the smallest value of J was determined as the most suitable model in each step. In order to determine the optimum number of hidden units in the ANN model with the combination of input variables determined above, the number of hidden units was varied from $(n-10)$ to $(n+10)$ with every combination of input variables, where n is the number of input units. The structure giving the smallest value of J was selected. In the present study, the average numbers of selected input and hidden units were 9 and 11, respectively.

(2) Evaluation of contralateral discrimination
In order to minimize the mis-discrimination of sinistral and dextral movements by the BCI, the decision by the ANN was revoked whenever the output value was in the range 0.4 to 0.6. When the output value was smaller than 0.4, the decision by the ANN was judged as a left elbow movement, and a result greater than 0.6 was judged as a right elbow movement. As mis-discrimination of the side of movement was considered to be more important than failure to detect the movement at all in an FES system, two indices were defined to evaluate the performance of the ANN model; the recognition rate ($\mathrm{R_{rate}}$) and the discrimination rate ($\mathrm{D_{rate}}$):

$$\begin{aligned}\mathrm{R_{rate}} = {} & (\text{number of data with outputs under 0.4} \\ & + \text{number of data with outputs over 0.6}) \\ & \div \text{total number of data}\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{D_{rate}} = {} & \text{number of correctly discriminated data} \\ & \div \text{number of recognized data}\end{aligned} \tag{5}$$

$$\begin{aligned}& \text{Total distinction rate} \\ & = \text{correctly distinguished data} \\ & \quad \div \text{total number of data}\end{aligned} \tag{6}$$

2.4 Confirmation of Discrimination Using the β Band

To prevent further mis-discrimination for safety in the practical use, it is necessary to confirm the discrimination results. Previous studies have shown that the β band power increases under mental load [19]–[21]. In the present study, this fact was intended to use for confirmation of correct discrimination, i.e. if the discrimination was not correct, we anticipated that the subjects increased the β band power to emphasize that the discrimination was not correct. To determine mental loads appropriate for increasing the β band power efficiently, EEGs were recorded while the subjects performed the following tasks.

Two types of tasks that could be solved within a short time were used as mental loads: mental calculation and association problems. The mental calculation problems consisted of:

1. Calculating arithmetic progressions.
2. Repeated subtraction of 7 from 1000.
3. Calculating the geometric progression of 2.

The association problems consisted of:

1. Last and first (choose a word with first letter the same as the last letter of a given word).

2. Listing names of animals, plants, vegetables, and colors.
3. Imagining disliked people or unpleasant things.

3. Results and Discussion

The efficiency of pre-treatment methods was examined using the EEG power ratio of the imaging period to the reference period (R_r/P_r or R_l/P_l) from 6 channels in the range 7 to 25 Hz. Using the model trained by the data for subject A without pre-treatment for evaluation using subject B, the R_{rate} was 38.6% and the D_{rate} was 94.3%. When pre-treatment was applied, the R_{rate} and D_{rate} were 94.4% and 92.1%, respectively. Furthermore, pre-treatment reduced the number of candidate input variables from 114 (19 frequency bands × 6 channels) to 57 (19 frequency bands × 3 comparative indices). The ANN was then trained for individual subjects and used for evaluating data obtained for other subjects. For convenience of calculation for ANN training, the 3 comparative indices in the range 10 to 19 Hz were selected, as most often selected by the PIM of the ANN models in the preliminary examination. Finally, 30 candidate input variables (10 frequency bands × 3 comparative indices) were selected for input into the ANN.

The discrimination results for all subjects are shown in Table 1. The model constructed using the data for the young normal subjects (under 50 years old) A, B, C, D, I, J and K, referred to as the young model, gave a R_{rate} of over 82.4% and a D_{rate} of over 80.0% (average total distinction rate: 83.6%) when evaluated using the same young normal subjects. The patient and senior models were constructed using the data for the three patients (subjects L, M and N, shown in bold text in Table 1) and the senior subjects E, F, G and H (aged over 50, shown in italics in Table 1). Using the patient and young models for evaluation using the three patients gave relatively low D_{rate}. Using the young, patient and senior models for evaluation using subjects E, F, G and H, gave a R_{rate} of 75.5% and a D_{rate} of 70.7% (average total distinction rate: 77.9%). These results suggest that the EEG is influenced by the age of the subjects.

Table 1 Examples of discrimination accuracies using EEG data for 10–19 Hz from the bilateral sensorimotor area, P3–P4 and T5–T6 with pre-treatment for all subjects.

Data for learning	Subject		Data for evaluation: A	B	C	D	*E*	*F*	*G*	*H*	I	J	K	**L**	**M**	**N**
	A	R_{rate}(%)	93.3	94.4	85.6	91.1	88.9	88.9	93.3	86.7	86.7	84.4	95.6	91.1	91.1	84.4
		D_{rate}(%)	93.3	92.1	93.3	95.6	88.9	91.1	93.3	88.9	97.8	93.3	86.7	86.7	93.3	91.1
	B	R_{rate}(%)	94.5	86.7	93.3	93.3	93.3	86.7	93.3	93.3	91.1	95.6	95.6	84.4	86.7	93.3
		D_{rate}(%)	94.2	93.3	85.7	92.8	***78.6***	82.0	80.9	88.1	85.4	83.7	90.7	84.2	82.0	90.5
	C	R_{rate}(%)	97.8	88.9	93.3	93.3	91.1	***77.8***	88.9	93.3	93.3	82.4	86.7	91.1	97.8	88.9
		D_{rate}(%)	95.6	88.9	86.7	93.3	80.0	88.9	91.1	91.1	97.8	84.4	88.9	82.2	86.7	88.9
	D	R_{rate}(%)	93.3	84.4	88.9	93.3	91.1	91.1	84.4	86.7	95.6	93.3	86.7	95.6	93.3	86.7
		D_{rate}(%)	93.3	91.1	80.0	93.3	88.9	91.1	91.1	88.9	93.3	88.9	91.1	88.9	84.4	93.3
	E	R_{rate}(%)	93.3	88.9	86.7	84.4	86.7	91.1	91.1	91.1	97.8	91.1	93.3	91.1	84.4	88.9
		D_{rate}(%)	88.9	84.4	84.4	91.1	93.3	84.4	84.4	86.7	86.7	84.4	84.4	88.9	88.9	93.3
	F	R_{rate}(%)	88.9	93.3	91.1	91.1	88.9	86.7	86.7	80.0	91.1	86.1	84.4	95.6	93.3	86.7
		D_{rate}(%)	87.5	83.3	82.9	87.8	85.0	87.1	82.0	88.9	82.9	89.7	86.8	88.4	83.3	92.3
	G	R_{rate}(%)	93.3	86.7	84.4	82.2	97.8	91.1	93.3	88.9	91.1	86.7	97.8	88.9	93.3	82.2
		D_{rate}(%)	93.3	86.7	84.4	88.9	82.2	88.9	93.3	86.7	95.6	84.4	88.9	82.2	91.1	82.2
	H	R_{rate}(%)	88.9	84.4	84.4	95.5	88.9	***75.5***	***75.5***	86.7	82.2	93.3	100	88.9	91.1	95.6
		D_{rate}(%)	95.1	92.1	84.2	88.4	***77.5***	***79.3***	91.1	93.3	***73.0***	85.7	91.1	82.5	80.5	***79.1***
	I	R_{rate}(%)	100	86.7	95.6	93.3	91.1	86.7	93.3	88.9	93.3	93.3	93.3	84.4	91.1	97.8
		D_{rate}(%)	93.3	86.7	88.9	91.1	***73.3***	82.2	95.5	88.9	93.3	84.4	88.9	84.4	86.7	84.4
	J	R_{rate}(%)	95.6	91.1	91.1	95.6	88.9	100	95.6	91.1	93.3	86.7	93.3	84.4	95.6	95.6
		D_{rate}(%)	88.9	86.7	97.8	95.6	84.4	95.6	97.8	86.7	97.8	87.1	100	***77.8***	91.1	88.9
	K	R_{rate}(%)	100	86.7	95.6	93.3	91.1	86.7	93.3	88.9	93.3	93.3	93.3	84.4	91.1	97.8
		D_{rate}(%)	93.3	84.7	88.4	90.5	***70.7***	***79.5***	95.2	87.5	83.3	88.1	93.3	81.5	85.4	84.0
	L	R_{rate}(%)	88.9	86.7	95.6	82.2	86.7	84.4	95.6	95.6	86.7	82.2	86.7	86.7	93.3	95.6
		D_{rate}(%)	91.1	86.7	80.0	91.1	84.4	86.7	91.1	86.7	93.3	82.2	84.4	86.7	82.2	91.1
	M	R_{rate}(%)	93.3	86.7	84.4	93.3	97.8	84.4	91.1	93.3	93.3	88.9	88.9	84.4	100	84.4
		D_{rate}(%)	92.8	87.2	89.5	88.1	***74.9***	86.8	82.9	85.7	88.1	85.0	97.5	81.5	87.1	84.2
	N	R_{rate}(%)	91.1	88.9	88.9	97.8	97.8	86.7	97.8	84.4	93.3	93.3	88.9	91.1	97.8	86.7
		D_{rate}(%)	91.1	84.4	86.7	88.9	91.1	91.1	86.7	93.3	91.1	95.6	84.4	82.2	88.9	93.3

Italics: normal subjects aged over 50, bold: patients with cervical spine injury.
Values in bold italics are under 80%.

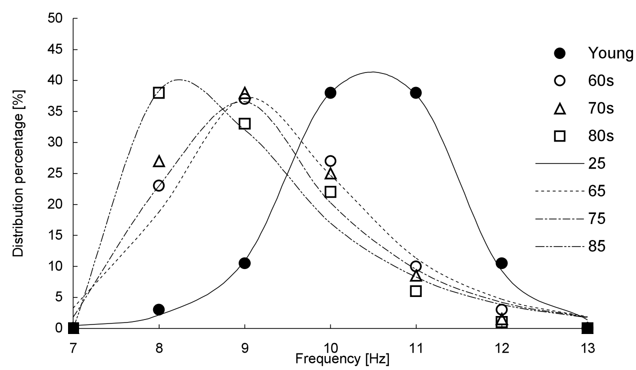

Fig. 4 Distribution of dominant frequency in the α band with respect to age. Actual data is plotted, and approximate distribution functions are shown as lines.

3.1 Influence of Age in the EEG

A decrease in the frequency of the α band in EEGs for elderly subjects in comparison to young adults has previously been pointed out [22]. The dominant α band frequency for young adults is about 10.8 Hz, whereas those for subjects in their sixties, seventies and eighties are 9.0 Hz, 9.0 Hz and 8.0 Hz, respectively [22]. Therefore, the dominant α band frequency decreases with age. The power values used in the present analysis are in the range 10–19 Hz, as suggested by the PIM results from the preliminary examination. This range may be suitable for young subjects, but data around 8 and 9 Hz seems to be important for elderly subjects. The authors attempted to interpolate the distribution of dominant frequency in the α band using the data of Okuma [22] as follows (see Fig. 4).

(1) Approximation of the frequency distribution
The distribution was approximated using the following asymmetric double sigmoidal function.

$$D_F = v \cdot \frac{1}{1+\exp\left(-\dfrac{x-u+w_1/2}{w_2}\right)} \cdot \left[1 - \frac{1}{1+\exp\left(-\dfrac{x-u+w_1/2}{w_3}\right)}\right] \tag{7}$$

where x is frequency, and u, v, w_1, w_2 and w_3 are parameters determined by the least mean square error of the measured points [22].

(2) Estimation of the relationship between parameters u, v, w_1, w_2, and w_3, and age N

To obtain the distribution function for an arbitrary age, the relationship between the parameters of the distribution function and age was determined by regression analysis. The derived relationship for u is expressed as

$$u = aN^2 + bN + c \tag{8}$$

The equations for the other parameters v, w_1, w_2, w_3 were determined in a similar manner.

Equation (7) was then recalculated using the parameters from Eq. (8) to obtain D_{Fi} at frequency i. Obtained distribution functions for 25, 65, 75, and 85 years old are shown as lines in Fig. 4. The following P_A value is defined as the representative power of the low-frequency bands.

$$P_A = \frac{1}{7}\left(\sum_{i=7}^{13} P_i \times D_{Fi}\right) \tag{9}$$

where P_i is the power for each frequency, and D_{Fi} is the value of the discrete distribution at frequency i, as calculated from Eq. (7).

The P_A value was used as an alternative to the power value at 10 Hz, and the P_A value and the power values from 11 Hz to 19 Hz were used as candidate input variables for the ANN. Since the P_A value is composed of frequency components from 7 Hz to 13 Hz, there is an overlap in the range of input from 11 Hz to 13 Hz. But this procedure will be suitable for treatment of both old subjects and young subjects equally. Table 2 shows the discrimination results using the P_A values when the ANN was trained for individual subjects then used for evaluation data for other subjects. When any data collected for the senior subjects (E, F, G, and H) were used for evaluation or learning, the R_{rate} and D_{rate} were higher than 88.9% (average total distinction rate: 93.8%). Changes in the dominant frequency in the α band were therefore successfully included in the P_A values, thereby eliminating the effect of age.

To further improve the discrimination accuracy, the total data collected for subjects A, D, H, I and M as a representative of young male, middle-aged male, senior male, young female, and patient, were used for learning. The discrimination results for use of this model on other subjects are shown in Table 3. All of the R_{rate} and D_{rate} were approximately 100% (average total distinction rate: 98.3%). Thus, very high D_{rate} were achieved by using a model based on EEG data collected from multiple persons representative of the variety of human EEG characteristics.

Adaptation of the model to temporal variance of the EEG was also investigated using three subjects (subjects A, D, and I). The ANN was trained using the data above and evaluated using data recorded on another day. The results are shown in Table 4. Without pre-treatment, the R_{rate} and D_{rate} for subject A were 63.6% and 89.8%. Pre-treatment without P_A values, the R_{rate} and D_{rate} increased to 88.9% and 84.4%.

Table 2 Discrimination accuracies using EEG data corrected according to the distribution of the dominant α band frequency for all subjects.

Data for learning		Data for evaluation													
Subject		A	B	C	D	*E*	*F*	*G*	*H*	I	J	K	**L**	**M**	**N**
A	R_{rate}(%)	93.3	100	93.3	100	100	95.6	97.8	95.6	93.3	97.8	93.3	88.9	91.1	95.6
	D_{rate}(%)	100	100	97.8	97.8	97.8	95.6	95.6	97.8	97.8	100	97.8	100	100	97.8
B	R_{rate}(%)	100	100	97.8	95.6	97.8	97.8	100	91.1	100	88.9	95.6	95.6	95.6	95.6
	D_{rate}(%)	97.8	93.3	97.8	97.7	97.8	95.5	97.8	100	97.8	97.5	97.7	97.7	95.4	100
C	R_{rate}(%)	97.8	97.8	100	97.8	100	93.3	95.6	100	97.8	95.6	95.6	91.1	100	95.6
	D_{rate}(%)	100	97.8	93.3	100	95.6	100	97.8	93.3	95.6	95.6	97.8	97.8	95.6	95.6
D	R_{rate}(%)	97.8	97.8	95.6	93.3	95.6	95.6	97.8	97.8	93.3	95.6	93.3	97.8	97.8	88.9
	D_{rate}(%)	97.8	97.8	95.6	100	97.8	95.6	95.6	97.8	97.8	97.8	95.6	97.8	93.3	93.3
E	R_{rate}(%)	93.3	100	97.8	100	100	97.8	97.8	95.6	93.3	97.8	95.6	97.8	93.3	100
	D_{rate}(%)	100	97.8	95.6	95.6	93.3	95.6	95.6	95.6	93.3	95.6	93.3	100	95.6	97.8
F	R_{rate}(%)	97.8	97.8	95.6	95.6	93.3	100	100	100	100	95.6	100	93.3	95.6	100
	D_{rate}(%)	95.5	100	95.4	100	95.3	100	97.8	95.6	97.8	95.4	91.1	92.8	100	93.3
G	R_{rate}(%)	93.3	100	93.3	88.9	97.8	95.6	100	93.3	97.8	97.8	100	100	97.8	91.1
	D_{rate}(%)	95.6	93.3	95.6	100	97.8	93.3	93.3	97.8	97.8	100	97.8	97.8	97.8	88.9
H	R_{rate}(%)	97.8	100	97.8	95.6	95.6	100	95.6	93.3	95.6	93.3	97.8	95.6	93.3	95.6
	D_{rate}(%)	93.1	95.6	97.8	95.4	100	93.3	97.7	93.3	97.7	95.3	95.5	97.7	95.3	95.4
I	R_{rate}(%)	97.8	100	95.6	97.8	100	95.6	97.8	100	100	97.8	100	100	97.8	97.8
	D_{rate}(%)	100	97.8	97.8	100	100	100	100	100	93.3	97.8	100	97.8	97.8	100
J	R_{rate}(%)	100	95.6	91.1	93.3	95.6	97.8	95.6	97.8	86.7	93.3	97.8	100	95.6	97.8
	D_{rate}(%)	97.8	100	97.8	97.8	97.8	93.3	97.8	97.8	100	93.3	97.8	97.8	97.8	93.3
K	R_{rate}(%)	97.8	100	95.6	97.8	100	95.6	97.8	100	97.8	100	93.3	100	97.8	97.8
	D_{rate}(%)	100	97.8	97.7	100	100	100	97.8	100	97.8	100	93.3	97.8	97.8	100
L	R_{rate}(%)	97.8	100	95.6	97.8	100	93.3	91.1	93.3	100	97.8	97.8	100	95.6	97.8
	D_{rate}(%)	91.1	91.1	97.8	97.8	100	95.6	100	100	97.8	97.8	97.8	93.3	93.3	95.6
M	R_{rate}(%)	100	91.1	91.1	100	93.3	97.8	100	100	100	93.3	100	100	93.3	93.3
	D_{rate}(%)	95.6	97.6	97.6	100	97.6	100	97.8	97.8	97.8	100	95.6	93.3	100	100
N	R_{rate}(%)	100	95.6	100	97.8	100	95.6	97.8	97.8	100	100	95.6	95.6	97.8	93.3
	D_{rate}(%)	97.8	100	95.6	97.8	95.6	95.6	95.6	97.8	95.6	93.3	97.8	97.8	97.8	100

Table 3 Discrimination accuracies using ANN model trained with data collected for subjects A, D, H, I and M.

Subject	R_{rate}	D_{rate}
B	100	97.8
C	97.8	100
E	100	97.8
F	100	100
G	100	100
J	95.5	100
K	100	100
L	100	97.8
N	97.8	100

Table 4 Discrimination accuracies for evaluation on different days.

	Subject	A	D	I
Without P_A values	R_{rate}	88.9	97.8	84.4
	D_{rate}	84.4	88.9	91.1
With P_A values	R_{rate}	97.8	97.8	100
	D_{rate}	100	100	100

Table 5 Averaged increase at C3, C4, P3 and P4 for power values in the range 14–20 Hz.

	Position			
Mental tasks	C3	C4	P3	P4
Calculation problems				
(1) Arithmetic addition (1+2+3)	81%	82%	23%	44%
(2) Subtraction (1000-7)	53%	43%	15%	18%
(3) Geometric progression (2^n)	83%	79%	32%	38%
Association problems				
(1) Last and first	**109%**	**119%**	**76%**	**90%**
(2) Disliked person	29%	58%	44%	51%
(3) Unpleasant thing	38%	73%	55%	65%
(4) Plants	51%	92%	52%	92%
(5) Colors	32%	44%	25%	41%
(6) Vegetables	67%	99%	61%	86%
(7) Animals	57%	51%	45%	63%

However, using the P_A values, the R_{rate} and D_{rate} increased to over 97.8% and 100% (average total distinction rate: 98.5%). Pre-treatment with P_A values is therefore effective for dealing with temporal variations in EEG patterns.

3.2 Confirmation of Operation Using the β Band

During the mental tasks, the β band power increased around the Pz position, predominantly at C3 and C4 [22]. Table 5 shows the averaged percentage increase at C3, C4, P3 and P4 for power values in the range 14–20 Hz. The β band power increased more during the association problems than during the mental calculation problems. In particular, for the "last and first" problem, the increase was 70% in each position, which is higher than for any of the other association problems. Therefore, the increase in the β band power for "last and first" problem was employed for confirmation of correct operation. If a response was wrong, the subject was asked to think about the "last and first" problem. Using this additional confirmation data, the discrimination accuracies were increased to almost 100%. As for other purposes with the allowance of error, the β band power increase could be used as the push button for selecting an item on a screen.

The system as proposed is suitable for use by amyotrophic lateral sclerosis patients to control input devices such as a cursor on a screen, allowing for choice selection and even written communication. This system may also be useful as a control method for hand orthoses for patients with severe motor impairment. Similarly, this system can be introduced into an FES system, which has been studied with respect to application to the reconstruction of lost movement functions. Although the system as proposed here functions only to distinguish between left and right movements from EEG patterns, it appears straightforward that similar processes can be applied for distinguishing between the imagined movement of the ankle or elbow, allowing full east-west and north-south movement suitable for cursor control.

4. Conclusion

The ERD from EEGs obtained for subjects imagining bending their elbow was analyzed by FFT and an ANN. It was found that ANN models constructed using EEG patterns for the period before movement could be used successfully to distinguish between left and right intended movements. Importantly, the present system was found to be generally applicable to all subjects ($D_{rate} > 95.5\%$) when trained using EEG data for a variety of subject categories (young, elderly, male, female, and handicapped). D_{rate} of greater than 93% were achieved by using the EEG from the left and right sensorimotor areas, P3–P4 and T5–T6 channels, modifying the dominant frequency of the α band according to a distribution, and pre-treating the EEG power data. Using an increase in the β band to confirm correct operation during training resulted in a further increase in recognition accuracy.

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