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journal or publication title	IEEE Transactions on Robotics
volume	21
number	4
page range	762-766
year	2005-08
URL	http://id.nii.ac.jp/1438/00009305/

doi: 10.1109/TRO.2004.842350

Electroencephalogram-Based Control of an Electric Wheelchair

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***Abstract*—This paper presents a study on electroencephalogram (EEG)-based control of an electric wheelchair. The objective is to control the direction of an electric wheelchair using only EEG signals. In other words, this is an attempt to use brain signals to control mechanical devices such as wheelchairs. To achieve this goal, we have developed a recursive training algorithm to generate recognition patterns from EEG signals. Our experimental results demonstrate the utility of the proposed recursive training algorithm and the viability of accomplishing direction control of an electric wheelchair by only EEG signals.**

***Index Terms*— Electroencephalogram-based control, electric wheelchair, direction control, recursive training algorithm.**

I. INTRODUCTION

THERE are numerous interfaces and communication methods between human and machines. A typical human-machine interface is to utilize input devices such as keyboards, mouse, joysticks, etc. Recently, a number of biological signals such as electromyogram (EMG) [1], electroencephalogram (EEG) [2], etc., have been employed as hands-free interfaces to machines (e.g., see [3–5]). In particular, the so called brain-computer interface (BCI) [6–10] has received significant attention. The BCI is a system that acquires and analyzes neural (brain) signals with the goal of creating a direct high bandwidth communication channel between the brain and the computer. Such systems are envisioned to have huge potentials for a wide ranging areas of research and applications such as brain (neural) signal acquisition and processing, bioengineering, and understanding the underlying neuroscience, to name a few. For systems and controls research, advances on brain-machine interfaces offer intriguing opportunities and challenges, for instance, brain control of machines.

There have been several studies using hands-free inputs in controlling machines through brainwaves. For example, speed and direction control of a small mobile robot using brainwaves and small facial muscular movements was reported in [11]. In this study, beta wave amplitude of EEG, jaw clench and eye muscle signal (electrooculogram, or EOG) are used to control the speed, forward/backward switching and the direction, respectively. In the system of [11], it is clear that the primary control signals for the mobile robot are jaw clench and eye muscle signals. The brainwaves is limited to control the speed of the mobile robot. The control objective was to move the mobile robot but without any specified or desired target positions. The paper did not report the success and/or failure rates of reaching the target positions. Bare [12] and Felzer [13] investigated wheelchair control using EOG and EMG, respectively. To the best of our knowledge, there has been no report of wheelchair control using only EEG in the literature.

In this paper, we investigate and demonstrate direction control of an electric wheelchair using only EEG signals. In addition, we present and discuss the success rate of reaching given target positions. Electric wheelchairs are some of the most important devices to assist physically handicapped persons. Our approach can be regarded as an advanced bio-control applications of BCI. Our experimental results for EEG-based control of an electric wheelchair show that the success rate of reaching target positions is about 80%.

II. EXPERIMENTAL SYSTEM

In this section, we introduce the experimental system for EEG control of an wheelchair. Figure 1 and Table I illustrate the EEG experimental set up and the experimental conditions, respectively. The experimental system consists of an electrocap (electrodes), electroencephalography (amplifier), an electrode box, an A/D converter and a computer. Figure 2 depicts electrode placement, where the thirteen points (circle) are selected according to the ten-twenty international electrode system [14]. We select both earlobes (A1 and A2) as reference electrodes.

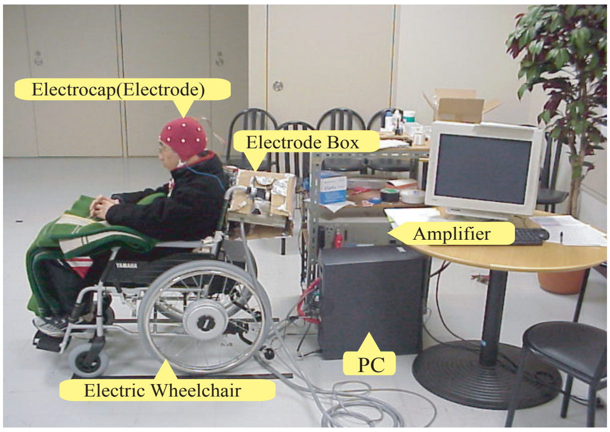

Fig. 1. Experimental System.

In the experiments, six healthy subjects that sit in the electric wheelchair are asked to think the direction (left or right) that they want to go. In this paper, the *left* and *right* direction thoughts are called *left thinking* and *right thinking*, respectively. Each subject is asked to perform 100 trials for the left thinking

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TABLE I
EXPERIMENTAL CONDITIONS.

Electrode placement	C3, C4, P3, P4, O1, O2, F7, F8 T3, T4, T5, T6, Fz (Fig. 2)
Reference electrodes	A1, A2 (Fig.2)
Sampling rate	1024 [Hz]
Sampling time	1.0 [s]
Bandpass filter	0.53 $\sim$ 30 [Hz]

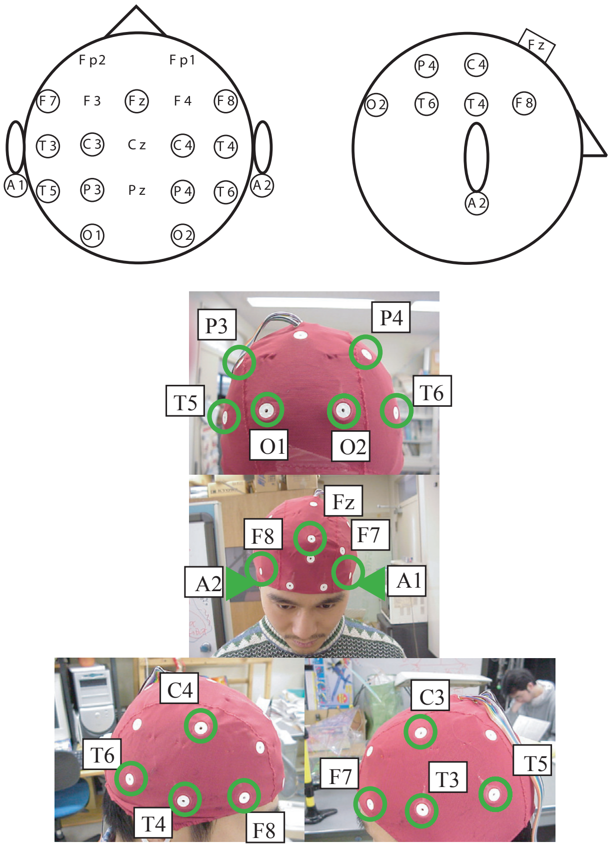

Fig. 2. Electrode placement (10-20 international electrode system).

and 100 trials for the right thinking. Half of the data (referred to as generating data) collected from each subject are used to generate a pattern for each subject. The remaining half of the collected data (referred to as checking data) collected are used to check the validity of the generated pattern. The detection time in each trial is 1 second. The sampling rate for detecting EEG is 1024 [HZ].

To avoid artifacts from EMG (and also EOG), we use the bandpass filer (as shown in Table I) with a pass band of 0.53 Hz to 30 Hz in the EEG detection. However, it is very difficult to perfectly reject the artifacts from EMG (and also EOG) even with the utility of the bandpass filer. Therefore, in our experiments, all the subjects are requested to minimize the movements of their bodies as well as eyes. It is possible to reduce artifacts from EOG and EMG by the requirement. With respect to EOG artifact, it is confirmed from preliminary experiments that the frequency peaks of EOG signals are less than 0.5 [Hz] under the requirement.

III. PATTERN GENERATION AND RECURSIVE TRAINING

In Section III-A we present a recognition pattern generation method using the generating data. Section III-B provides a recursive training procedure to optimize recognition patterns.

In previous papers [15–17], we have recommended to generate an individual recognition pattern for each subject since differences among EEGs of subjects are quite large. In this paper, an individual recognition pattern will be generated for each subject as well.

A. Pattern generation and pattern matching

In this section, we describe a new recognition pattern generation method using the generation data.

Let brainwave signals detected from thirteen electrodes in the kth generating data ($k = 1, 2, \cdots, 100$) be

$$f_1^k[t], f_2^k[t], \cdots, f_{13}^k[t] \;\; t = 1, 2, \cdots, 1024. \quad (1)$$

We represent FFT results for the time domain data (1) as (2).

$$F_1^k[n], F_2^k[n], \cdots, F_{13}^k[n] \;\; n = 1, 2, \cdots, 38. \quad (2)$$

The coefficient of correlation between electrodes i and j is obtained as

$$R^k_{(i,j)} = \frac{\sum_{n=1}^{38}(F_i^k[n] - \overline{F_i^k})(F_j^k[n] - \overline{F_j^k})}{(38-1)S^k_{Fi}S^k_{Fj}}, \quad (3)$$

where $\overline{F}_i^k$ and $\overline{F}_j^k$ are the average values of $F_i^k[n]$ and $F_j^k[n]$, respectively. S^k_{Fi} and S^k_{Fj} are the standard deviations of $F_i^k[n]$ and $F_j^k[n]$, respectively. By calculating correlations among all the electrodes, we obtain the following correlation coefficient matrix:

$$\mathcal{R}^k = \begin{pmatrix} R^k_{(1,1)} & R^k_{(1,2)} & \cdots & R^k_{(1,13)} \\ R^k_{(2,1)} & R^k_{(2,2)} & \cdots & R^k_{(2,13)} \\ \vdots & \cdots & \ddots & \vdots \\ R^k_{(13,1)} & R^k_{(13,2)} & \cdots & R^k_{(13,13)} \end{pmatrix}. \quad (4)$$

Since the matrix is symmetric, we generate the pattern vector P^k by selecting the upper triangular elements excepting the diagonal elements. The pattern vector P^k consists of 78 elements.

$$\begin{aligned} P^k &= (p_1^k, p_2^k, \cdots, p_{77}^k, p_{78}^k) \\ &= (R^k_{(1,2)}, R^k_{(1,3)}, \cdots, R^k_{(12,11)}, R^k_{(12,13)}) \quad (5) \\ & k = 1, 2, \cdots, 100 \end{aligned}$$

As the collected data include both the left thinking and the right thinking, the recignition patterns for left thinking and right thinking (i.e., left pattern vector Pl^k and right pattern vector Pr^k) are generated separately.

The final left and right recognition patterns Vl and Vr are obtained by calculating the average for all the generating data. Here notations pl^k_m and pr^k_m denote the mth elements of the vectors Pl^k and Pr^k, respectively, where m = 1, 2, $\cdots$, 78. Notations vl_m and vr_m denote the mth elements of the vectors Vl and Vr, respectively.

$$\begin{aligned} Vl &= (vl_1, vl_2, \cdots, vl_{77}, vl_{78}) \\ Vr &= (vr_1, vr_2, \cdots, vr_{77}, vr_{78}), \end{aligned} \tag{6}$$

where

$$\begin{aligned} vl_m &= \frac{1}{50}\sum_{k=1}^{50} pl^k_m, \\ vr_m &= \frac{1}{50}\sum_{k=1}^{50} pr^k_m, \\ m &= 1, 2, \cdots, 78. \end{aligned}$$

The pattern matching using the final left and right recognition patterns proceeds as follows. First, we generate a pattern vector Vx from the checking data (unknown data) in the same way as in (1)-(6). Next, we calculate the Euclidean distances between Vx and Vl as well as between Vx and Vr.

$$Ll = \sqrt{(Vl - Vx)(Vl - Vx)^T} \tag{7}$$

$$Lr = \sqrt{(Vr - Vx)(Vr - Vx)^T} \tag{8}$$

Ll denotes the distance between an unknown pattern and the final left thinking pattern. Lr denotes the distance between an unknown pattern and the final right thinking pattern. Left or right thinking is selected according to the distances, i.e., the left thinking is selected when $Ll < Lr$, and the right thinking is selected when $Ll > Lr$.

B. Recursive training

In this section we present a recursive training procedure to optimize recognition patterns. In the recursive training algorithm, ρ denotes the number of the iterations. ρ_{max} denotes the maximum iteration number. In this paper, $\rho_{max} = 10$. $E_L(\rho)$ and $E_R(\rho)$ denote the recognition rates [%] for the left and right thinkings using the checking data at the ρth iteration, respectively. $Vl(\rho)$, $Vr(\rho)$, $Ll(\rho)$ and $Lr(\rho)$ denote Vl, Vr, Ll and Lr at the ρth iteration, respectively. As addressed above, an individual recognition pattern is generated by applying the recursive training algorithm to each subject.

[Recursive training algorithm]

(Step 1)

$\rho = 1$.

(Step 2)

Record EEG through the 100 trials for the left thinking and the 100 trials for the right thinking. Divide the recorded data into generating data and checking data.

(Step 3)

Generate left thinking and right thinking pattern vectors $Vl(\rho)$ and $Vr(\rho)$ using (1)-(6).

(Step 4)

Calculate $Ll(\rho)$ and $Lr(\rho)$ from the checking data via (7) and (8). According to the pattern matching results, calculate the recognition rates $E_L(\rho)$ and $E_R(\rho)$ at the ρth iteration.

(Step 5)

If $E_L(\rho) > E_{max}$ and $E_R(\rho) > E_{max}$ then $\rho_E = \rho$ and go to Step 8 else go to Step 6.

(Step 6)

If $|E_L(\rho) - \frac{E_L(\rho-1)+\cdots+E_L(\rho-s+1)}{s}| < \Delta E$ then $\rho_E = \rho$ and go to Step 8 else go to Step 7.

(Step 7)

If $\rho = \rho_{max}$ then $\rho_E = \rho$ and go to Step 8 else $\rho = \rho + 1$ and go back to Step 2.

(Step 8) The trained patterns for the left and right thinkings are $Vl(\rho_E)$ and $Vr(\rho_E)$, respectively. The recognition rates for the checking data are $E_L(\rho_E)$ and $E_R(\rho_E)$, respectively.

In the electric wheelchair control, we use $E_{max} = 70$ [%], $s = 3$ and $\Delta E = 10$ [%]. A final pattern for each subject is generated through the recursive training. Table II shows the recognition rates $E_L(\rho_E)$ and $E_R(\rho_E)$ of six subjects (Subjects A-F) for the checking data. The average recognition rate is about 80 [%].

TABLE II

RECOGNITION RATES THROUGH RECURSIVE TRAINING.

	Recognition Rate (%)	
Subject	E_L	E_R
A	73	88
B	85	47
C	91	81
D	76	88
E	74	79
F	74	85
Ave.	79 (%)	78 (%)

IV. ELECTRIC WHEELCHAIR CONTROL

Figures 3 and 4 show the experiment workspace. The experiment workspace consists of 28 regions. Each region is 60 [cm] $\times$ 90 [cm]. The colored regions in Figure 4 show the target positions (LEFT goal and RIGHT goal). According to the pattern matching results shown in Section III-A, the electric wheelchair is moved to the region A (the left direction) or the region B (the right direction) from the initial position (start). The subjects are required to approach the target positions by repeating the movement. The electric wheelchair can arrive at the target positions when the number of incorrect direction decisions is less than or equal to one and the number of correct direction decisions is three. Therefore the success rate of reaching the target positions is about 31.2[%] if the direction (left or right) decision is random.

In the experiment, the wheelchair is stopped during the EEG detection and the pattern matching since the processing time is several seconds. According to the pattern matching result, the

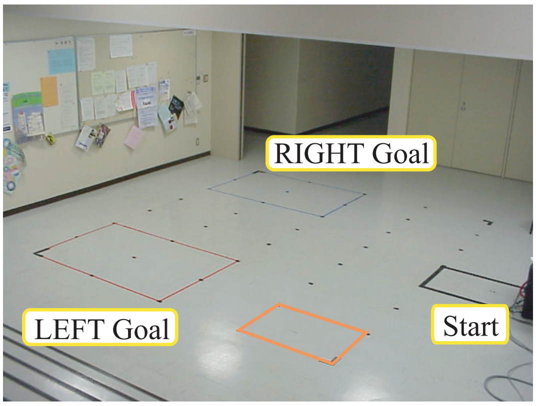

Fig. 3. Experiment Workspace (Photo).

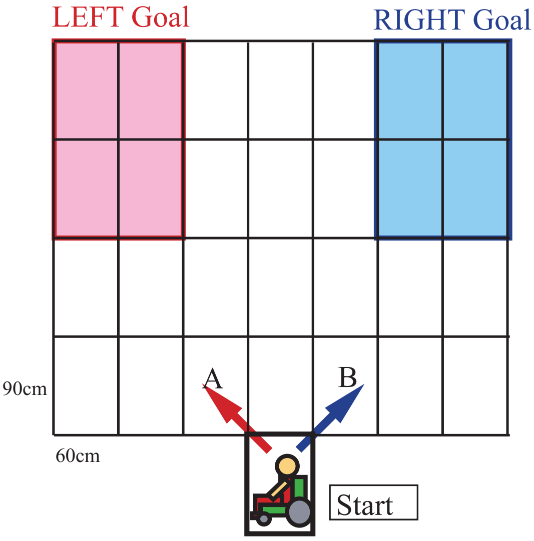

Fig. 4. Experimental Workspace.

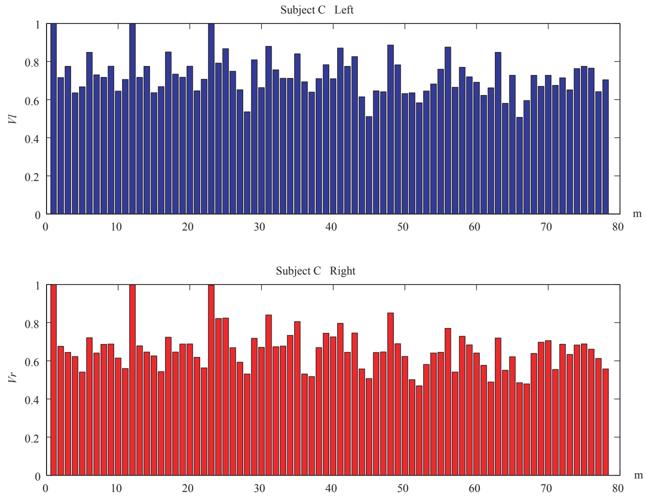

Fig. 5. Generated Recognition Pattern (Subject C).

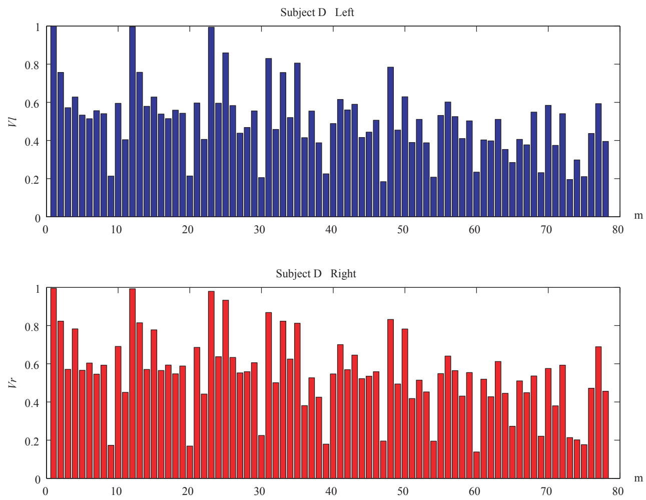

Fig. 6. Generated Recognition Pattern (Subject D).

electrical wheelchair is moved to the next region. The procedure is repeated until the wheelchair reaches target position or until the number of incorrect directions is more than one.

Figures 5 and 6 show the recognition patterns for the left and right thinkings of the subjects C and D, respectively. In the figures, the horizontal and vertical axes denote the element number m and the elements $(Vl_m(\rho_E)$ and $Vr_m(\rho_E))$, respectively. These patterns are generated through the recursive training described in Section III. The patterns of Subjects C and D are quite different. This fact shows that it is quite reasonable to generate an individual recognition pattern for each subject.

Using the generated recognition patterns, 20 control trials (the 10 LEFT goal trials and 10 RIGHT goal trials) for each subject are performed. Figure 7 shows an experimental result. Table III shows the success rates for reaching the target positions. The average success rate is about 80%. This shows viability of EEG-based control for an electric wheelchair. The exception if the low successful rate of $Right$ for the subject B.

TABLE III
SUCCESS RATES.

Subject	Success Rate(%) Left	Success Rate(%) Right
A	80	90
B	90	20
C	100	100
D	80	100
E	80	80
F	70	90
Ave.	83(%)	80(%)

Research is ongoing to further improve the success rates of all subjects.

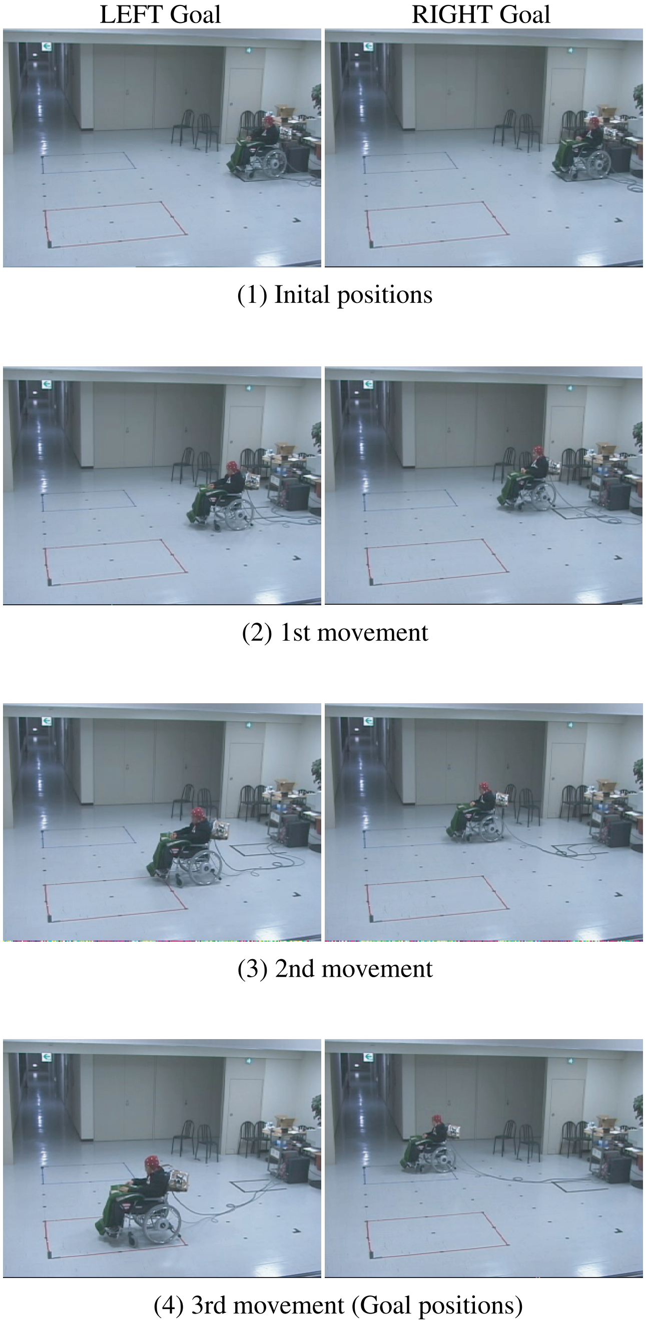

Fig. 7. Experiment Results.

V. Conclusion

This paper investigates control of an electric wheelchair by electroencephalogram (EEG) signals. This represents an attempt to control machines via brain signals. In this research, the goal is to control the direction (left or right) of the electric wheelchair by only EEG signals. To do so, we have developed a recursive training algorithm to generate recognition patterns from EEG. The experimental results are quite encouraging and demonstrate the utility of the pattern recognition algorithm and the viability of controlling wheelchairs by only EEG signals.

Acknowledgment

We would like to thank Mr. Koki Kubo of the University of Electro-Communications for his contribution to this research.

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