Electroencephalogram Analysis of Mechanisms Underlying Brain Activity during Voluntary Movement

Nobuhisa Kuramoto, Shin-Ichi Ito, Katsuya Sato, and Shoichiro Fujisawa

***Abstract*—This paper proposes an electroencephalogram (EEG)-based method for identifying the mechanism underlying brain activity during a voluntary movement. Our final goal is to develop a rehabilitation assistance system that can be used on a daily basis by observing a patient's degree of functional recovery. In order to assist in ambulation rehabilitation, the mechanism related to the voluntary movement need to be identified. As a first step, we elucidated the mechanism underlying brain activity. The proposed method involves EEG recording, blind source separation, noise reduction, and feature enhancement. The EEG device has dry-type sensors. Independent component analysis is used to delink the signal. Median morphological filters are used to reduce EEG noise and emphasize the feature signal. To demonstrate the effectiveness of the proposed method, we conducted experiments using real EEG data.**

***Index Terms*—Electroencephalogram (EEG), voluntary movement, brain activity, independent component analysis, median morphological filters, decision making.**

I. Introduction

In this paper, we propose an electroencephalogram (EEG)-based method for detecting the trigger pattern of a walking motion. It is difficult to develop robot-assisted walking devices for the elderly and people with hemiparesis. Our final goal is to develop a rehabilitation assistance system that can assist in ambulation exercise and be used on a daily basis for monitoring of a patient's degree of functional recovery. In order to assist in ambulation rehabilitation, the method needs to detect the feature signal related to the voluntary walking in the EEG. The techniques that target various EEG features exist for analyzing EEG signals [1], such as power spectrum, spectral centroid, event-related potential (ERP), and principal component analysis (PCA) as well as factor analysis, independent component analysis (ICA), k-nearest neighbor (kNN), linear discriminant analysis (LDA), neural network analysis (NN), and support vector machine (SVM) classification. We focused on a combination of feature extraction techniques for real-time processing because our final goal is to develop a system that can be used on a daily basis. As a first step, we detected an EEG feature signal that has the potential to become the starting point of a walking motion using SVM after morphological filtering [2]. Therefore, we detected an EEG signal obtained in the pre-frontal region (AF3, F7, F3, F4, F8, and AF4), temporal cortex (T7, T8), and association area of the motor cortex (FC5, FC6) using an EPOC device when a human makes a voluntary movement of the right and left knee. In a recent study, the mechanism of voluntary movement was confirmed using fMRI (functional MRI) [3]. Nonetheless, the mechanism of voluntary movement was not confirmed using EEG in that study [3]. Therefore, we studied the mechanism of voluntary movement using both fMRI and EEG. Then, using ICA, we recovered independent sources using only sensor observations that are linear mixtures of independent source signals [4]–[8] after detecting an EEG signal. Finally, we detected the signal that has a peak value, either positive or negative, using a median morphological filter [9], [10]. On the basis of the signals detected using ICA and the median morphological filter, we scanned activities of the prefrontal and temporal cortex related the decision making [11], [12] and activities of the association area of the motor cortex related to voluntary movement. In addition, we obtained activities of the frontal cortex that are related to decision making and voluntary movement for imaging, information processing, and verifying stored informationbased on the results of the experiment with a voluntary movement of the right or left knee. These results suggest that we could confirm the mechanism of voluntary movement using EEG similar to that using fMRI. These data indicate that we could develop a novel rehabilitation assistance system, serving the same purpose as the following systems: hybrid assistive limb (HAL) developed by Cyberdyne Inc. [13], and the wearable power-assist locomotor (WPAL) built by Aska Corporation [14]. The new system could use EEG analysis on a daily basis.

II. Proposed Methods

The method involves EEG recording, blind source separation, noise reduction, and feature enhancement.

A. EEG Recording

In EEG recording, we used the EPOC device, which was developed by EMOTIV, to measure EEG activity. The EPOC uses a dry-type sensor and covers 10ch electrodes. The two reference electrodes are attached to the bone just behind each ear lobe and the exploring electrodes are attached to AF3, AF4, F7, F8, F3, F4, T7, T8, FC5, and FC6 in the international 10-10 system (Fig. 1) because activities of the prefrontal and temporal cortex include potentials related to decision making [11], [12]. In addition, activities of the association area of the motor cortex contain potentials related to regulation of motion. Moreover, this device has high resolution, neuro-signal acquisition, and a processing wireless neuro-headset. During EEG feature extraction, the

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EEG data are sent to a computer through a serial port. The sampling rate is 126 Hz.

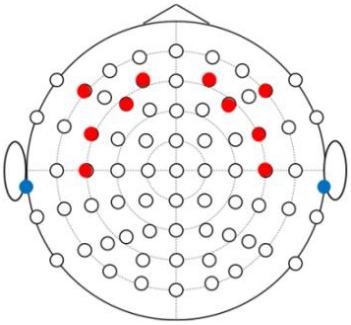


Fig. 1. The international 10-10 system. EEG is recorded from the frontal cortex, temporal cortex, and association area of the motor cortex (AF3, AF4, F7, F8, F3, F4, T7, T8, FC5, and FC6) in the international 10-10 system (red dots). The two reference electrodes are attached to the bone just behind each ear lobe (blue dots).

B. Blind Source Separation

The goal of blind source separation (BSS) is to recover independent sources using only sensor observations that are linear mixtures of independent source signals. The term blind indicates that both the source signals and the way the signals were mixed are unknown. ICA is a method for solving the blind source separation problem and identifies a linear coordinate system such that the resulting signals are as statistically independent from each other as possible [4]. Here, ICA is defined by the following formula:

$$y(t) = W \times x(t) \tag{1}$$

After solving this equation, we performed the blind signal separation and whitening of the observed signal.

1) Whiting of the observed signal

The convergence of independent components is a suitable stage for whitening of the observed signal.This is because whitening allows for inclusion of uncorrelated and independent components. This process builds the whitening matrix so that the vector of the observed signal is uncorrelated with the variance–covariance matrix of the observed signal [5]. The whitening matrix is determined as the eigenvectors used by the variance–covariance matrix of the normalized data of the observed signal. Here the variance–covariance matrix is a matrix showing the magnitude of the deviation degree of the average value [6] as follows:

$$V_{ij}^2 = \frac{1}{n-1}\sum_{k=1}^{n}(X_{ik} - \bar{X}_i)(X_{jk} - \bar{X}_j) \tag{2}$$

$$C = [V_{ij}^2] \tag{3}$$

where X_{ik} and X_{jk} are sample data of the matrix, and $\bar{X}_i$ and $\bar{X}_j$ are average values of the matrix. The whitening matrix is calculatedas eigenvectors from these formulae using the Jacobi method [7].

2) Blind signal separation

At this point, there is no independence and the arbitrary property of rotation remains in the state resulting from whitening of the observed signal. Therefore, blind signal separation is determined as the optimal return matrix using unitary transformation [5]. Here, an evaluation function such as the index of independence is necessary when blind signal separation is calculated as the optimal return matrix. As the evaluation function, we used the Kullback–Leibler (KL) divergence:

$$KL(W) = \int p(y) \log \frac{p(y)}{\prod_k p(y_k)} dy \tag{4}$$

We employed the method of steepest descent for determining minimum W for KL divergence as follows:

$$\varphi(y) = -\left(\frac{\partial \log p(y_1)}{\partial y_1}, \cdots, \frac{\partial \log p(y_1)}{\partial y_1}\right)^T \tag{5}$$

$$W_{t+1} = W_t + \eta(I - \varphi(y)y^t)W_t \tag{6}$$

The convergence point of W integrates the separation matrix formulation and reproduces the independent signal when measuring the RAWsignal by applying W to the observed signal [5], [8]. In that case, we arrived at a rectangular matrix starting from the square matrix using singular value decomposition. Fig. 2 and Fig. 3 show the properties and frequency characteristics, respectively, of ICA.

C. Noise Reduction and Feature Enhancement

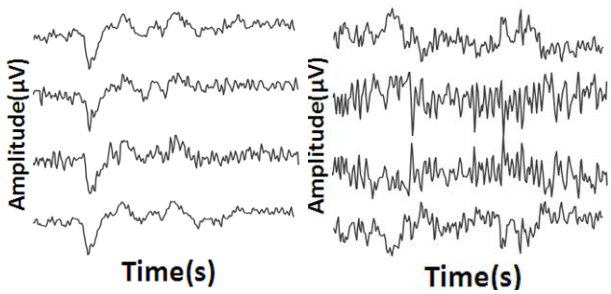
Median morphological filters with edge enhancement and smoothing properties were used to reduce EEG noise and emphasize the feature signal. The morphological filters use Minkowski addition and subtractionbased on a morphological operation and are defined by the following formulae:

$$f'^{(t)} = \begin{cases} f(t)_m & n \text{ isodd numbers } m = \frac{(n+1)}{2} \\ \frac{f(t)_m + f(t)_{m+1}}{2} & n \text{ is even number } m = \frac{n}{2} \end{cases} \tag{7}$$

$$[f' \oplus g](t) = \max_{\substack{t+u \in F \\ u \in G}}\{f'(t-u) + g(u)\} \tag{8}$$

$$[f' - g](t) = \min_{u \in G}\{f'(t-u) - g(u)\} \tag{9}$$

where *f*(*t*) is the original wave,$f(t)_m$ is a measured value of each case inthe original wave, n is a window of the filter, m is a median value [9], *g*(*t*) is the structure function to determine the assignment of different filters, *G* and *F* are aggregates, and *u* and *t* are components of the aggregates.



(a) (b)

Fig. 2. Properties of independent component analysis. Panels a) and b) are an observed signal and ICA applied to the observed signal, respectively.

The basic operation of morphological filters involves 4 interrelated functions: erosion, dilation, opening, and closing. These functions are expressed as follows:

Erosion:

$$[f' - g^s](t) = \min_{u \in G}\{f'(t+u) - g(t)\} \quad (10)$$

Dilation:

$$[f' \oplus g^s](t) = \max_{\substack{t+u \in F \\ u \in G}}\{f'(t+u) + g(t)\} \quad (11)$$

Opening:

$$f'_g(t) = [(f' - g^s) \oplus g](t) \quad (12)$$

Closing:

$$f^g(t) = [(f' \oplus g^s) - g](t) \quad (13)$$

Here, $g^s(t) = g(-t)$. Erosion has the effect of bloating in both negative and positive directions. Opening $\left(f_g(t)\right)$ of set f with set g is erosion followed by a Minkowski addition, and closing $\left(f^g(t)\right)$ is dilation followed by a Minkowski subtraction. In this study, opening was applied to the EEG data if $f(t) > 0$. Closing was applied if $f(t) < 0$ [10]. Fig. 4 and Fig. 5 show the properties and frequency characteristics, respectively, of the morphological filters.

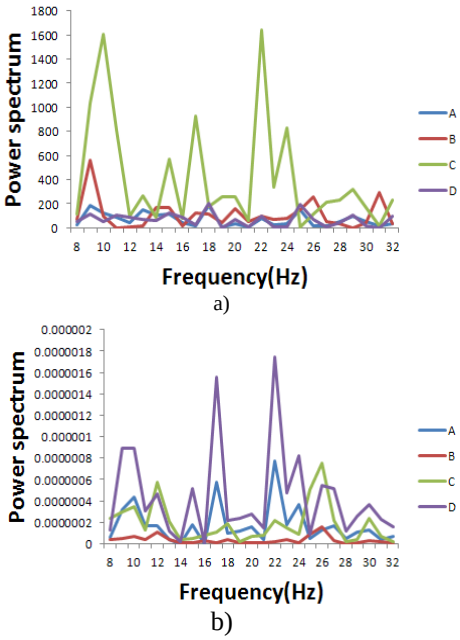


Fig. 3. Frequency characteristics of independent component analysis (ICA). Panels a) and b) are an observed signal and ICA applied to the observed signal, respectively. A – D are a sample signal from Fig. 2.

III. Experiments

Five males (average age 22 years) served as subjects. Fig. 6 shows a schematic of the experiments. The study proceeded as follows: The subjects wore the EPOC device and a sleep shade. Next, the subjects sat on a chair and closed their eyes. For each set, EEG data were recorded for 10 s with no motion and 4 s during voluntary movements. The motion pattern was the movement of the right or left foot up and then down. Fig. 7 through Fig. 10 present the results. Horizontal and vertical axes are time and amplitude, respectively. The values of a channel and sampling point are 10 and 256, respectively. The values of the sliding overlap and window are 1 and 15, respectively.

IV. Result and Discussions

From the recording during the voluntary movement of the right knee, we scanned activity of the prefrontal cortex (AF3 and AF4) at the beginning, based on the results presented in Fig. 7 and Fig. 9. Then, we assessed activity of the temporal cortex (T7 and T8). These results suggest that we could confirm the activity of decision making from the prefrontal and temporal cortex when a subject heard a sound signal. We scanned activity of the right frontal cortex (F8 and F4). It was possible to identify the activity related to the EEG pattern when the subject made the voluntary movement of the right knee [15]. Then, we assessed activity of the left frontal cortex (F7 and F3). We could confirm the activity related to decision making and voluntary movement from the left frontal cortex before the subject moved the right foot up and down. Finally, we scanned activities of the association area of the motor cortex (FC5 and FC6). The result indicates that we could confirm the activity related to the voluntary movement from the association area of the motor cortex before the subject moved the right foot up and down. However, in the results of voluntary movement of the left knee, we assessed activity of the left prefrontal region (AF3, F7, and F3) at the beginning, based on the results shown in Fig. 8 and Fig. 10.

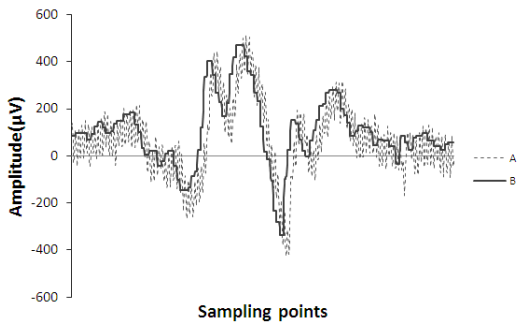


Fig. 4. Properties of the median morphological filter.A and B correspond to the input signal and filtering results, respectively.

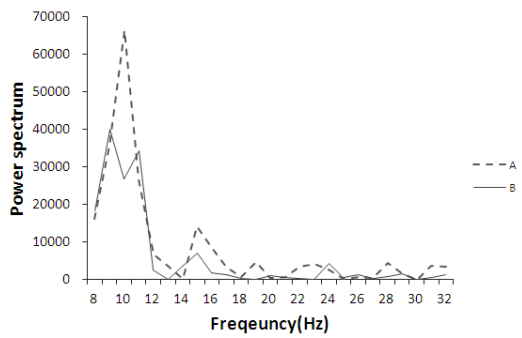


Fig. 5. Frequency characteristics of the median morphological filter.A and B correspond to the input signal and filtering results, respectively.

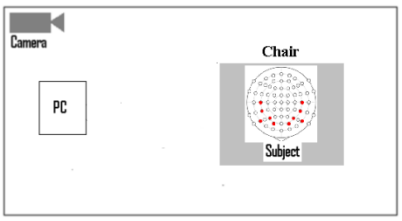


Fig. 6. Experimental settings for recording of EEG signals. EEG data are sent by the EPOC device to a PC.

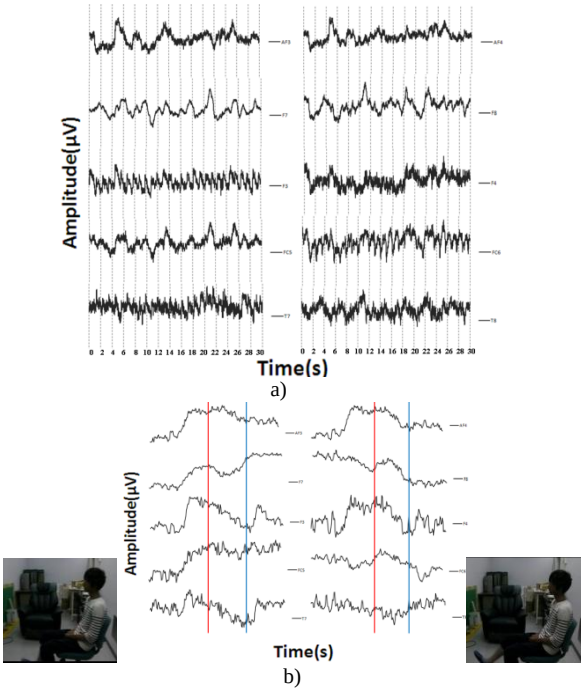


Fig. 7. An observed signal of a voluntary movement of the right knee; a) and b) are EEG data for a set and sample data from 4 s to 6 s, respectively.

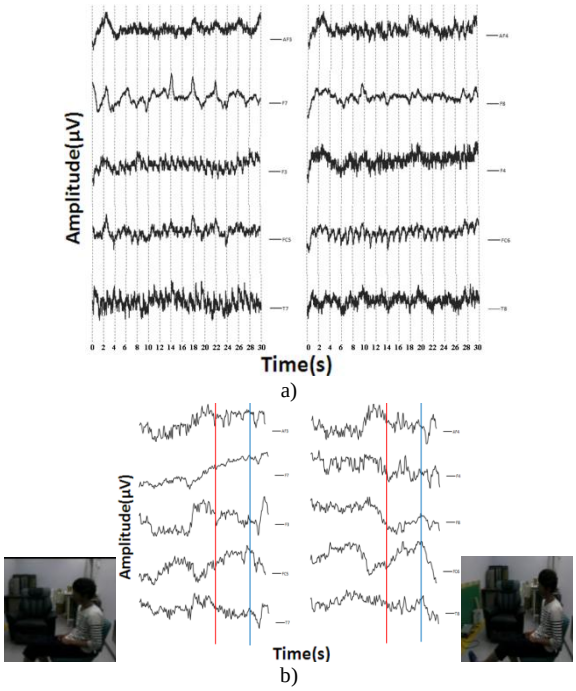


Fig. 8. An observed signal of a voluntary movement of the left knee; a) and b) are EEG data for a set and sample data from 4 s to 6 s, respectively.

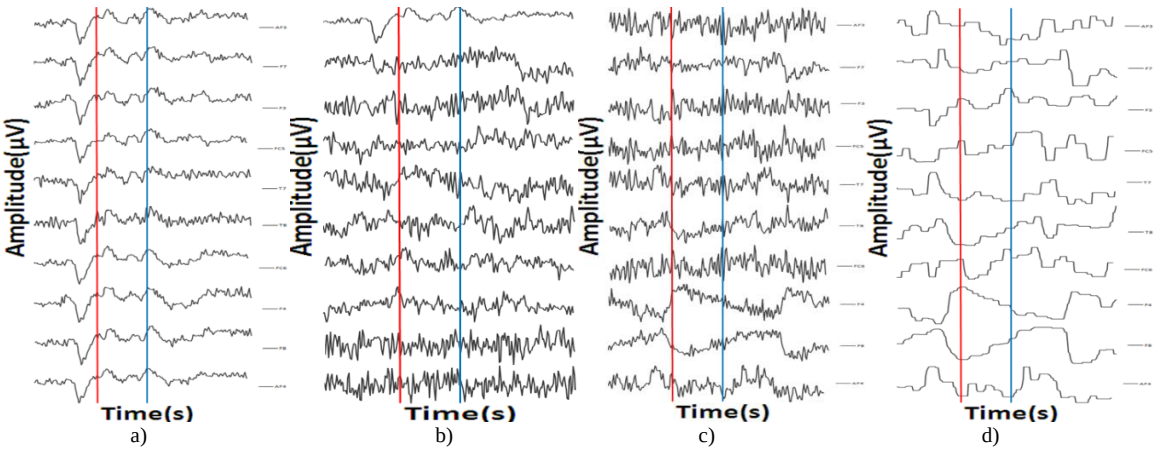


Fig. 9. The results of a voluntary movement of the right knee; (a) through (d) are an observed signal, whitening signal, ICA applied to the observed signal, and the median morphological filter after ICA, respectively. The red line and blue line are a start and end line, respectively.

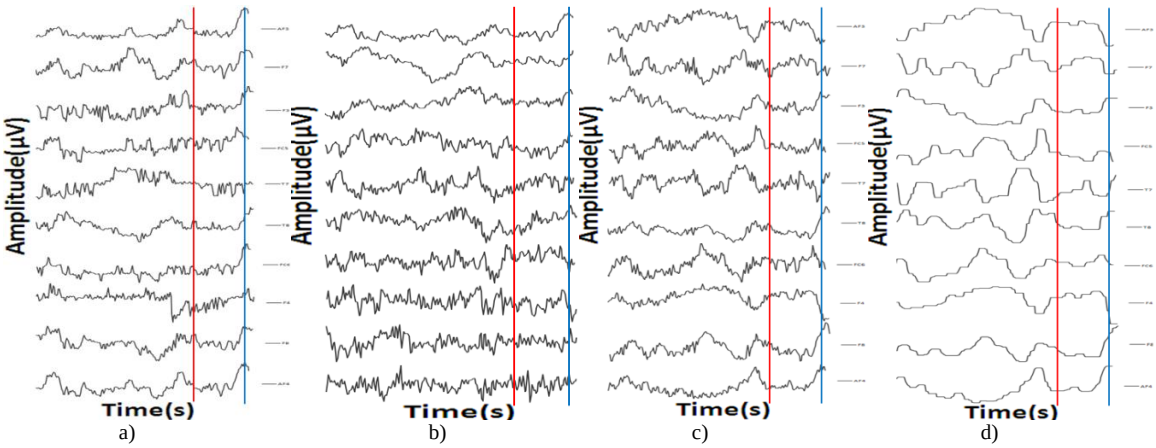


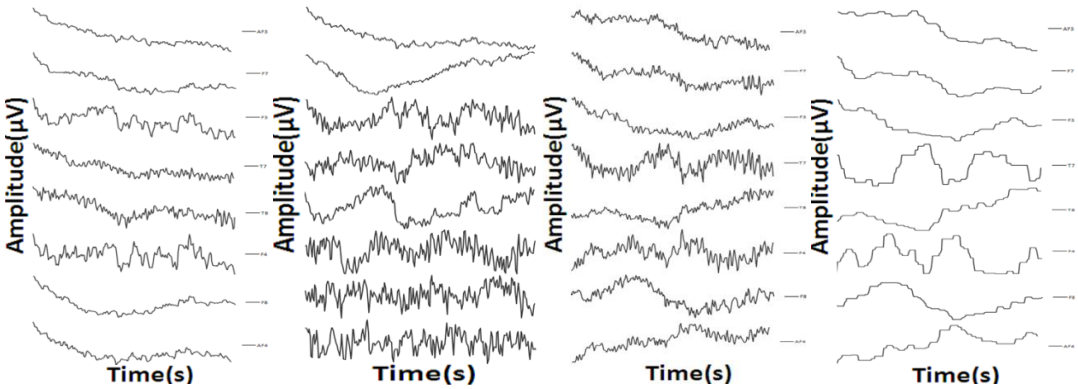
Fig. 10. The results of a voluntary movement of the left knee; a) through d) are an observed signal, whitening signal, ICA applied to the observed signal, and the median morphological filter after ICA, respectively. The red line and blue line are a start and end line, respectively.

We could confirm the activity related to the information processing and verification of stored information from the left prefrontal region when the subject heard the sound signal.We scanned activity of the right prefrontal cortex (AF4) and assessed activity of the temporal cortex (T7 and T8). These results suggest that we could confirm the activity of decision making from the right prefrontal and temporal cortex after the activity related to the information processing and verification of stored information [15]. Then, we scanned activity of the right frontal cortex (F8 and F4). We could

confirm the activity related the decision making and voluntary movement from the right frontal cortex before the subject moved the left foot up and down. Finally, we determined activities of the association area of the motor cortex (FC5 and FC6). We could confirm the activity related the voluntary movement from the association area of the motor cortex before the subject moved the left foot up and down. These data show that identifying a mechanism of voluntary movement using EEG could become as effective as the fMRI-based method.

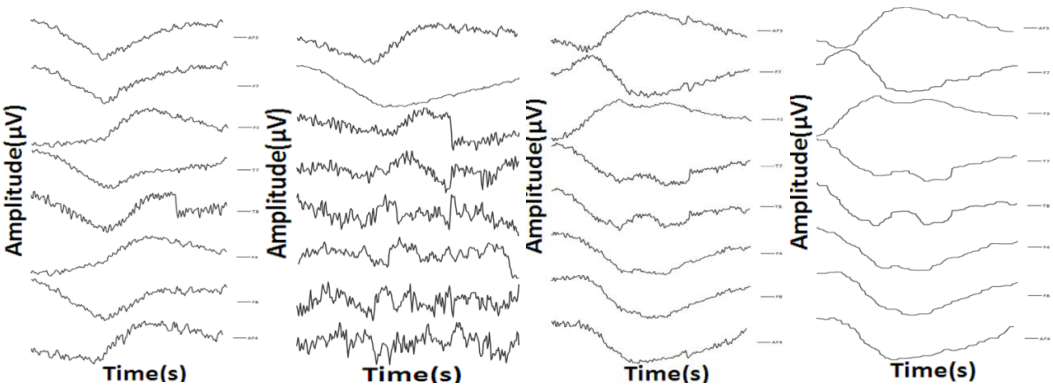
Next, we conducted the experiment with a voluntary movement of the right or left knee because we had to confirm the frontal cortex (F7, F3, F4, and F8) activities related to the movement of the right foot up and down as well as the information processing and verification of stored information during the movement of the left foot up and down, respectively. Fig. 11 and Fig. 12 show the results of the experiment with the voluntary movement of the right or left knee. According to these results, we could confirm the unique activity of the frontal cortex without the voluntary movement of the right or left foot. In addition, the correlation coefficient between the voluntary movement and the absence thereof in the frontal cortex activity was approximately 0.6 (Fig. 13). These results indicate that we could confirm the frontal cortex activities related to the movement of the right foot up and down as well as the information processing and verification of stored information during the movement of the left foot up and down.

Nevertheless, the results differed among the subjects. Fig. 14 presents the data on the mechanism underlying brain activity when each subject made the voluntary movement. We obtained analogous data on the activity of the prefrontal cortex (AF3 and AF4; Fig. 14). The right-handed subjects showed switching of activity from AF4 to AF3 during a voluntary movement of the right knee, and switching from AF3 to AF4 during a voluntary movement of the left knee. On the other hand, the left-handed subjectshowed the activity at the same instant.



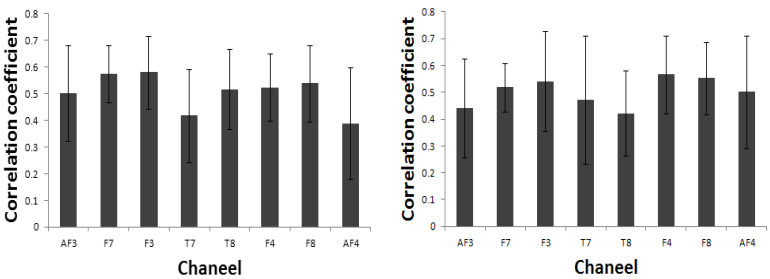
a) b) c) d)

Fig. 11. The results of the voluntary movement of the right knee; a) through d) are an observed signal, whitening signal, ICA applied to the observed signal, and the median morphological filter after ICA, respectively.



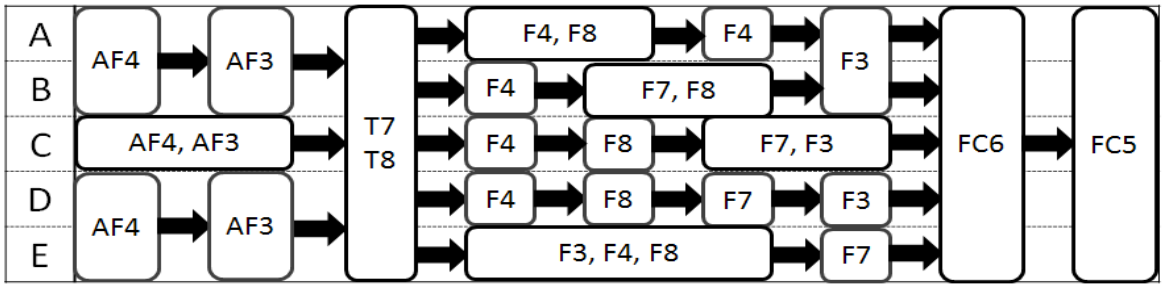
a) b) c) d)

Fig. 12. The results of the voluntary movement of the left knee; a) through d) are an observed signal, whitening signal, ICA applied to the observed signal, and the median morphological filter after ICA, respectively.

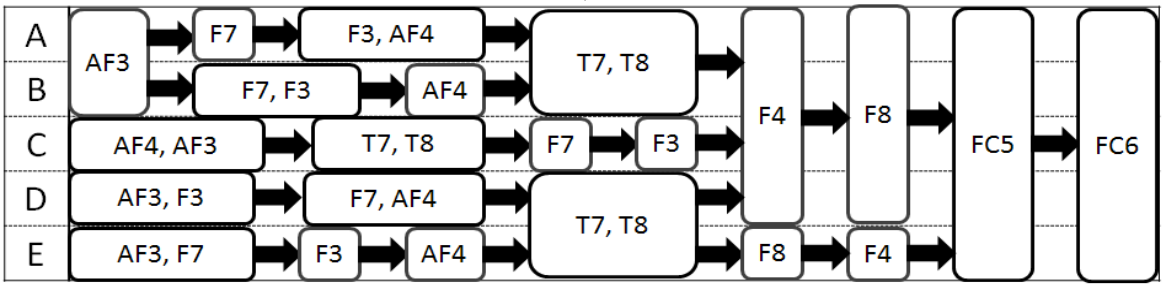


a) b)

Fig. 13. The correlation coefficient of the median morphological filter after ICA of the observed signal. Panels a) and b) show the data on a voluntary movement of the right knee and a voluntary movement of the left knee, respectively.

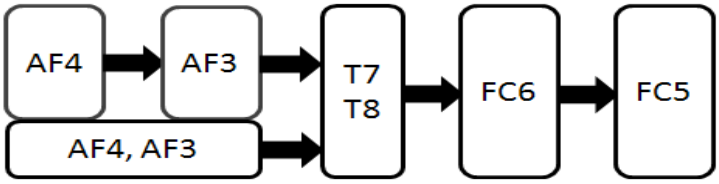


a)

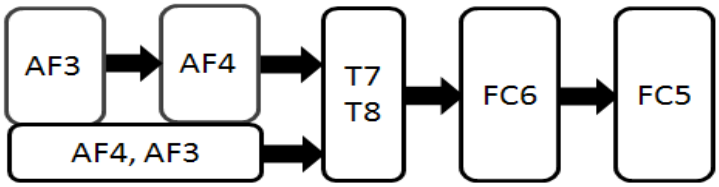


b)

Fig. 14. The mechanism underlying brain activity when each subject made a voluntary movement. Panels a) and b) show the mechanism associated with the right knee and that of the left knee, respectively. Subjects A, B, D, and E are right handed, whereas subject C is left handed.



a)



b)

Fig. 15. The rule of quantitative evaluation in 6ch; (a) and (b) show the mechanism associated with the right knee and that of the left knee, respectively.

These results suggest that it is possible to obtain similar results when we compare right-handed and left-handed subjects. Moreover, we obtained similar data on activity of the temporal cortex (T7 and T8). The temporal cortex shows brain activity of decision making at this very instant. Furthermore, the subjects exhibited switching from FC6 to FC5 (the association area of the motor cortex) during the voluntary movement of the right knee and switching from FC5 to FC6 during the voluntary movement of the left knee. It appears that the association area of the motor cortex conducts information processing from side to side as an activity related to voluntary movements. In addition, we observed changes of activity in the frontal cortex (F7, F8, F3, and F4) in each subject. During a voluntary movement of the right knee, activity of the frontal cortex was registering between the temporal cortex (T7, T8) and the association area of the motor cortex (FC5, FC6). Thus, it is possible to distinguish the activity related to decision making and voluntary movement (F7, F3) and the brain activity when the subject made a voluntary movement of the right knee (F8, F4) [15] in each of our subjects. On the other hand, in the data on the voluntary movement of the left knee, activity of the frontal cortex was registering between the temporal cortex (T7, T8) and the association area of the motor cortex (FC5, FC6) in the left-handed subject. Thus, it is possible to distinguish the activity related to decision making and voluntary movement (F8, F4) and the information processing and verification of stored information (F7, F3) [13] in each subject. However,activity of the left frontal cortex (F7, F3) was registering between the left prefrontal cortex (AF3) and the right prefrontal cortex (AF4) in the right-handed subject. It appears that activity of the left frontal region (AF3, F7, and F3) was registering before the activity of decision making. More than 90% of the brain-related language is located in the left brain of right-handed people [16]. In contrast, 60% of the brain-related language is located in the left brain and 40% in the right brain of left-handed people [16]. These results indicate that it is possible for the left prefrontal region to evolve in a right-handed person. Accordingly, the left frontal region activity registered before the decision making activity. We conducted quantitative evaluation to confirm the above conclusions. We applied the rule of quantitative evaluation as shown in Fig. 14 and Fig. 15. In addition, we used SVM for EEG pattern classification. SVM classifies the EEG patterns that indicate the presence or absence of a voluntary movement of the right or left foot (up and down).This study employs a linear discriminant function $y = f(x)$,which identifies two classes of the variable x, for hyperplane as

follows:

TABLE I: THE RESULTS OF QUANTITATIVE EVALUATION IN EACH SUBJECT IN 10CH BASED ON THE MECHANISM FROM FIG. 14

	Right	Left
Detection	$0.700(\frac{18}{28}+\frac{19}{28}+\frac{23}{28}+\frac{21}{28}+\frac{17}{28})$	$0.692(\frac{19}{28}+\frac{18}{28}+\frac{25}{28}+\frac{18}{28}+\frac{17}{28})$
False detection	$0.021\left(\frac{125+130+124+119+137}{6160}\right)$	$0.020\left(\frac{120+125+118+133+123}{6160}\right)$

TABLE II: THE RESULTS OF QUANTITATIVE EVALUATION IN ALL SUBJECTS IN 6CH BASED ON THE MECHANISM FROM FIG. 15

	Right	Left
Detection	$0.714(\frac{100}{140})$	$0.728\ (\frac{102}{140})$
False detection	$0.019\left(\frac{118}{6160}\right)$	$0.019\left(\frac{116}{6160}\right)$

$$\mathrm{y} = \mathrm{sgn}[a \cdot x + b] \tag{14}$$

$$a \cdot x = a_1 \cdot x_1 + \cdots a_n \cdot x_n \tag{15}$$

$$\mathrm{sgn}[u] = \begin{cases} 1 \cdots \mathrm{u} \geq 0 \\ -1 \cdots \mathrm{u} \leq 0 \end{cases} \tag{16}$$

$$\max_{a,b} \min_i \frac{|a \cdot x_i + b|}{\|a\|} \tag{17}$$

where a and b are slope and intercept, respectively. The criteria for determining the identified classes of hyperplane data establish the maximized margins. Here, a margin is the Euclidean distance between the plane of identification and the training data. We identified the peak data either positive or negative and used nonpeak data of either positive or negative maximal margin classifier [17], [18]. The values of the sliding overlap and window are 1 and 30, respectively, for classifying the EEG patterns. The number of detection patterns and test data patterns is 28 and 6160, respectively. In addition, this paper detects the real mechanism obtained peak data of voluntary movement (Detection) and the real mechanism obtained peak data of no motion (False detection), respectively, as follows:

$$Detection = \frac{RMDetNum}{TotalMovNum} \tag{18}$$

$$False\ detection = \frac{NRMDetNum}{TotalNum} \tag{19}$$

where $TotalMovNum$ and $TotalNum$ means the total number of voluntary movement and test data to evaluate, respectively. $RMDetNum$ and $NRMDetNum$ denote the automatically-discriminated numbers ofreal mechanism obtained peak data of voluntary movement and the real mechanism obtained peak data of no motion, respectively.

Table I shows the results of the quantitative evaluation in each subject in 10ch based on the mechanism from Fig. 14. In addition, Table II shows the results of the quantitative evaluation in all subjects in 6ch based on the mechanism from Fig. 15. The detection ratio was 0.700 during a voluntary movement of the right knee and 0.692 during a voluntary movement of the left knee (Table I). The detection ratio during the voluntary movement of the right knee was not due to the prefrontal cortex peak being late or the right frontal cortex peak showing a change. It appears that the activity of decision making became sluggish, and the activity related to the decision making and voluntary movement (F7, F3) and the EEG pattern when the subject made a voluntary movement of the right knee (F8, F4) [15] were changed because the subject became familiar with the process of moving the right or left foot up and then down.

Similarly, the detection ratio during the voluntary movement of the left knee was not due to the prefrontal cortex peak's being late or the left frontal cortex peak showing a change. It appears that the activity of decision making became sluggish, the activity related to the decision making and voluntary movement (F7, F3) and the EEG pattern when the subject made the voluntary movement of the right knee (F7, F4) [15] were changed in the left-handed subject. The activity of decision making (AF3, AF4) and the EEG pattern when the subject made the voluntary movement of the right knee (F7, F4) [15] were changed in the right-handed subject because the subject became familiar with the process of moving the right or left foot up and then down. Moreover, the false detection ratio was 0.0206 during the voluntary movement of the right knee and 0.0201 during the voluntary movement of the left knee (Table I). These results show that the EEG pattern during the movement of the right or left foot up and then down bears resemblance to the peak of voluntary movement. In addition, there is some analogy between the signals of the peak of voluntary movement and the signals corresponding to no movement.

The detection ratio was 0.714 during the voluntary movement of the right knee and 0.728 during the voluntary movement of the left knee (Table II). The detection ratioduring the voluntary movement of the right knee and the voluntary movement of left knee were not due to the prefrontal cortex peak being late or the quantitative evaluation in each subject. It appears that the subjects became familiar with the process of moving the right or left foot up and then down. In addition, the false detection ratio was 0.019 during the voluntary movement of the right knee and 0.019 during the voluntary movement of the left knee (Table II). These results indicate that the EEG pattern during the movement of the right or left foot up and down bears resemblance to the peak of voluntary movement. Similarly, there is some analogy between the signals of the peak of voluntary movement and the signals corresponding to no movement. If we compare the results of Tables I and II, the difference in the detection ratio was 0.004 during the voluntary movement of the left knee. The quantitative evaluation in all subjects appears to be successful at detecting the pattern of AF3 > AF4 because the right-handed subjects showed activity in the left prefrontal region (AF3, F7, and F3) before the activity of the right prefrontal cortex (AF4).

All these results suggest that we could confirm the activity of decision making and that related to voluntary movement from the activities of the prefrontal cortex, temporal cortex,

and association area of the motor cortex in all subjects. Accordingly, we may be able to develop a rehabilitation assistance system that works on a daily basis and utilizes EEG analysis. Nevertheless, the peak of the prefrontal cortex was registering late because the subjects became familiar with the process of moving the right or left foot up and then down. We believe that the EEG pattern of the frontal region was changed because this brain region did not activate itself for the integration of the processing when humans voluntarily move the right or left knee [19] during the latter half of our experiment.In future, we aim to develop a method to turn on the activity of the frontal region in a sustainable manner.

V. Conclusion

As a first step in the development of a rehabilitation assistance system based on EEG analysis, we elucidated the mechanism underlying brain activity when each subject made a voluntary movement. The new system may assist in ambulation rehabilitation using EEG data from the prefrontal cortex, temporal cortex, and association area of the motor cortex. We could confirm the EEG activity related to decision making and the activity related to a voluntary movement of the right or left foot up. ICA can be used for the blind source separation in EEG, and the median morphological filter can be used for noise reduction in EEG during the movement of the right or left foot up. Future work should lead to the development of the rehabilitation assistance system that works on a daily basis and uses EEG analysis. Therefore, we should be able to find a way to activate the frontal region in a sustainable manner, improve the detection ratio, reduce false detection, and create a real-time measuring and processing program.

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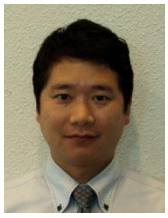

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