Discrimination of Hand and Elbow Movements Using Entropy of ECoG

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Abstract—In this paper, a method of estimating hand and elbow movements using electrocorticogram (ECoG) signals is proposed. Using multiple channels, surface electromyogram (EMG) signals and ECoG signals were obtained from patients simultaneously. The estimated movements were those to close and then open the hand and those to bend the elbow inward. The patients were encouraged to perform the movements in accordance with their free will instead of after being induced by external stimuli. Surface EMG signals were used to find movement time points, and ECoG signals were used to estimate the movements. To extract the characteristics of the individual movements, the ECoG signals were divided into a total of six bands (the entire band and the δ, θ, α, β, and γ bands) to obtain the information entropy, and the maximum likelihood estimation method was used to estimate the movements. The results of the experiment showed the performance averaged 74% when the ECoG of the gamma band was used, which was higher than that when other bands were used, and higher estimation success rates were shown in the gamma band than in other bands. The time of the movements was divided into three time sections based on movement time points, and the “Before” section, which included the readiness potential, was compared with the “Onset” section. In the Before section and the Onset section, estimation success rates were 66% and 65%, respectively, and thus it was determined that the readiness potential could be used.

Keywords—ECoG, gamma band, entropy, maximum likelihood estimation, readiness potential.

I. INTRODUCTION

The Brain-Computer Interface (BCI) is a study area for interactions between the brain and the computer. Since this is controlled using the brain’s electrical activities, this is useful for those that have difficulties in moving due to muscle damage [1]. Methods of measuring the brain’s electrical activities can largely be divided into two types: invasive methods and noninvasive methods. The electroencephalogram (EEG), which is a widely used noninvasive method, generates severe noises due to the skull and the scalp and provides low spatial resolutions. On the other hand, the electrocorticogram (ECoG), which is an invasive method, provides high spatial resolutions and signal to noise ratios (SNR).

Recently, in ECoG data-based BCI studies, studies to estimate actual movements or imaginations of movements were conducted. At Beijing Normal University College of Education, the movements of the ring finger of the left hand and the tongue were estimated using independent component analysis (ICA), k-means clustering, and the affinity propagation algorithm based on ECoG signals generated when the movements of the ring finger of the left hand and the tongue were imagined. Doctor Songmin Jia’s research team extracted the characteristics of ECoG signals generated when the movements of the little finger of the left hand and the tongue were imagined using principal component analysis (PCA). They also estimated the movements of the little finger of the left hand and the tongue using three algorithms: support vector machine (SVM), cross-validation, and common spatial pattern (CSP). Thereafter, they compared the estimation success rates of individual algorithms with each other [4]. At Northeastern University, relative wavelet energy (RWE) and PCA were used to extract the characteristics of ECoG signals, and the probabilistic neural network (PNN) algorithm was used to estimate the movements of the little finger of the left hand and the tongue [5]. Studies using information entropy, histograms, or changes in the power of certain bands were also conducted.

Brainwaves can be divided into five bands: 0∼3Hz (delta δ), 4∼7Hz (theta θ), 8∼13Hz (alpha α), 14∼30Hz (beta β), and 31∼100Hz (gamma γ). In particular, studies on emotions and behavior using the gamma band have been conducted frequently [2]. One study indicated that the power of ECoG signals generated due to behavior increases in the gamma band and that this change is related with changes in cortices [2,3]. To classify the extracted characteristics, studies have been conducted using diverse methods, such as k-nearest neighbors (KNN), linear discriminant analysis (LDA), and artificial neural networks (ANN) [3-5].

In the present study, a method of estimating actual movements from inputs of unknown ECoG signals based on ECoG signals generated when epilepsy patients make movements to close their hands or bend their elbows is proposed. The time of the movements was divided into three sections based on movement time points, and the characteristics of the signals were extracted using information entropy. The
three sections included a section in which the readiness potential (used to reduce system delays) was observed. Based on the movement time points, the section from -0.75 sec. to -0.25 sec. was set as the “Before2” section, the section from -0.5 sec. to +0 sec. as the “Before1” section, and the section from -0.25 sec. to +0.25 sec. as the “Onset” section, and the lengths of all the sections were the same at 0.5 sec. Probabilistic models were made based on the statistical characteristics of the information entropy obtained from each section, and actual movements were estimated using the maximum likelihood estimation method.

In this paper, Section II describes the methods used to obtain ECoG signals and methods used to process the signals, and Section III describes the experimental results. Finally, Section IV draws conclusions.

II. METHODS

A. Signal recording

To acquire ECoG signals, a sampling frequency of 200 Hz or 400 Hz was used depending on the subject, and the signals were 60 Hz notch filtered in order to remove power cable noises.

The signals were acquired from two subjects. Subject A was a 25-year-old woman, and 72 ECoG channels were used on her left hemisphere, and one electromyogram (EMG) channel was used on her elbow and one on her hand. The sampling frequency used was 200 Hz. Subject B was a 37-year-old man, and 58 ECoG channels were used on his right hemisphere, and one EMG channel was used on his elbow and one on his hand. The sampling frequency used was 400 Hz. Two movements were made: “movements to close and then open the hand (hand)” and “movements to bend and then straighten the elbow (elbow)”. The movements were performed in self-paced mode to determine the time points of movements in accordance with the subjects’ free will. The experiment was conducted for approximately three hours per day, and after practicing first, the movements were repeated several to several hundred times. When one movement was completed, the other movement was performed using the same method. To prevent the subjects from becoming tired, the subjects were allowed to take a sufficient rest every time when the experiment had continued for around 10 minutes.

B. ECoG signal modeling

Using the surface EMG signals recorded simultaneously with ECoG signals, the movement time points of the individual subjects were predicted. In the case of Subject A, 130 hand-closing movements and 119 elbow-bending movements could be predicted, and in the case of Subject B, 87 hand-closing movements and 85 elbow-bending movements could be predicted.

The “Before2”, “Before1”, and “Onset” section setting method is shown in Fig. 2. Among the three sections, the ECoG signals of a section that should be analyzed are indicated by \( x_{c,m}[n] \), where \( c \) indicates channels and \( m \) indicates movements.

To extract the characteristics of the individual movements, information entropy (\( H \)) was used. Information entropy is a concept presented to measure the amount of information necessary to indicate signals, which is a method of measuring the level of uncertainty of stochastic variables. Information entropy \( H(X) \) is defined as follows:

\[
H(X) = - \sum_{k=1}^{K} p(x_k) \times \log_2 p(x_k)
\]

where \( X \) is a stochastic variable that can have values \( \{x_1, x_2, \cdots, x_K\} \). \( p(x_k) \) refers to \( \Pr(X = x_k) \) and satisfies the conditions set forth by (2) and (3).

\[
0 \leq p(x_k) \leq 1
\]

\[
\sum_{k=1}^{K} p(x_k) = 1
\]

Probability \( p(x_k) \) can be calculated using the following expression:

\[
p(x_k) = \frac{\text{number of } \in I_k}{\text{number of total sample}}
\]

\[
I_k = \{n \mid (k-1) \times M + x_{\min} \leq x[n] < k \times M + x_{\min}\},
\]

\[
k = 1, 2, \cdots, K
\]

where \( K \) determines the number of range \( I_k \) by which the samples of \( x_{c,m}[n] \) are divided and \( M \) is calculated through (5).

\[
M = \frac{x_{\max} - x_{\min}}{K}
\]

\( x_{\max} \) refers to the maximum value among all ECoG signals, and \( x_{\min} \) refers to the minimum value. The entropy ECoG signals \( x_{c,m}[n] \) can be shown as follows:
For one movement \( m \), one entropy value can be generated by each ECoG channel. Using \( H_{c,m} \) obtained from multiple independent movements of the subject, a histogram of entropy was obtained, and the statistical characteristics of the entropy were examined. In Fig. 3, the horizontal axis indicates the entropy, and the vertical axis indicates the frequencies of occurrence of the relevant entropy. Since the distribution of the frequencies is similar to Gaussian distribution, the distribution was modeled using the Gaussian probability density function.

To predict models for the two movements in each section, the average of the information entropy obtained from the \( c \)th channel of movement \( m \) was obtained and compared. In Fig. 4, individual circles represent averages, and channel 1 is on the bottom left followed by higher-number channels in an upward order with channel 10 in the upper left. The upper-right circle is channel 58.

The probability density function \( f_{c,m}(t) \) obtained from the \( c \)th channel of movements \( m \) can be obtained using the variance and mean of the information entropy of \( L \) pieces of training data.

\[
H_{c,m} = -\sum_{k=1}^{K} p_{c,m}(x_k) \times \log_2 p_{c,m}(x_k)
\]  

(6)

C. Maximum likelihood estimation method

The entropy probability densities by channel of individual movements can be analyzed using the likelihood function of the multidimensional probability density function. Under the assumption that ECoG signals by channel are probabilistically independent from each other, the entropy probability densities by channel of individual movements can be indicated by multiplications of one-dimensional probability densities and can be indicated by the (8), where \( ch \) is the number of ECoG channels. By taking logarithms of both sides, the

\[
\hat{m} = \arg \max_m \left( \prod_{c=1}^{ch} f_{c,m}(t \mid m) \right) = \arg \max_m \left( \sum_{c=1}^{ch} \log(f_{c,m}(t \mid m)) \right)
\]  

(8)

III. RESULTS

The performance of movements was predicted using surface EMG signals, and from the results, it was identified that Subject A independently performed the movement to close her hand 130 times and the movement to bend her elbow 119 times, and Subject B independently performed the two movements 87 times and 85 times, respectively.

To measure the estimation success rate of the proposed algorithm, training data and test data were divided in a ratio of 2:1 and used. One thousand combinations were randomly selected to conduct the experiment repeatedly, and the average value was obtained. Using band pass filters, the experiment was conducted on a total of six bands: the entire band and the delta (\( \delta \)), theta (\( \theta \)), alpha (\( \alpha \)), beta (\( \beta \)), and gamma (\( \gamma \)) bands. The experiment was conducted using the same method in each of the “Before2”, “Before1”, and Onset sections. The
experimental results showed an average estimation success rate of 60.24±0.16% for Subject A and an average estimation success rate of 62.19±0.21% for Subject B. When seen by band, Subjects A and B showed estimation success rates of 67.56±0.01% and 77.42±0.14% respectively in the gamma band. These estimation success rates were higher than those shown in the entire band and other bands.

When the readiness potential was used in the entire band, Subject A showed estimation success rates of 56.04±0.11% and 55.82±0.10% in the “Before1” and “Before2” sections, respectively, which were lower (by 4.20% and 4.42%, respectively) than the Onset section. Subject B showed estimation success rates of 60.66±0.01% and 69.43±0.16% in the “Before1” and “Before2” sections, respectively. The estimation success rate in the “Before1” section was 1.53% lower than the Onset section, and the estimation success rate in the “Before2” section was 7.25% higher than the Onset section.

Subject B showed estimation success rates of 70.43±0.13% and 66.74±0.12% in the “Before1” and “Before2” sections, respectively. The estimation success rate in the “Before1” section was 0.82% lower than that in the Onset section, and the estimation success rate in the “Before2” section was 7.25% higher than that in the Onset section.

Subject B showed estimation success rates of 76.64±0.14% and 76.64±0.12% in the “Before1” and “Before2” sections, respectively, which were 0.78% lower than the Onset section. Based on these results, it was determined that the readiness potential could be used.

IV. CONCLUSION

In the present study, the characteristics of ECoG signals were extracted based on information entropy, and a method to estimate finger-bending movements and elbow-bending movements using the maximum likelihood estimation method was proposed. Repeated experiments conducted in a total of six bands consisting of the entire band and delta through gamma bands revealed 4-7% higher estimation success rates in the gamma band than in other bands. Based on these results, it was determined that many pieces of information on behavior existed in the gamma band, and this is consistent with the results of previous studies. If the method is implemented as a real-time system, system delays can be reduced using the readiness potential.

REFERENCES

Abstract— We characterize the hemodynamic response changes in the main olfactory bulb (MOB) of anesthetized rats with near-infrared spectroscopy (NIRS) during the presentation of three different odorants: (i) plain air as a reference (Blank), (ii) 2-heptanone (HEP), and (iii) isopropylbenzene (Ib). Odorants generate different changes in the concentrations of oxy-hemoglobin. Our results suggest that NIRS technology might be useful in discriminating various odorants in a non-invasive manner using animals with a superb olfactory system.

Keywords— brain-machine interface (BMI), functional near-infrared spectroscopy (fNIRS), main olfactory bulb (MOB), Oxy-hemoglobin (HbO₂), Beer–Lambert law, maximum likelihood estimation (MLE).

I. INTRODUCTION

NEAR infrared spectroscopy (NRIS) is a technique that enables the noninvasive measurement of concentration changes and optical coefficients (scattering and absorption coefficients) in chromophores, such as Oxy-hemoglobin (HbO₂), Deoxy-hemoglobin (Hbr), myoglobin, cytochrome oxidase, water, lipid, and protein, in human tissues using lights that are harmless to the human body. Since Jobsis first measured tissue oxygenation in human tissues [1], NRIS has been used extensively not only in the analysis of the metabolic process in human tissues, including neuroimaging, which visualizes brain activation; the diagnosis of breast cancer; neuroscience using small animals; and brain-machine interfaces (BMI), but also in the analysis of crop quality. In particular, near infrared rays in wavelengths of 600–900 nm have fewer occurrences of scattering and absorption in human tissues compared with other wavelengths. Thus, information inside the human body can be obtained using these rays.

Concentration changes in HbO₂ and Hbr are due to hemodynamic responses in blood vessels. An increased amount of HbO₂ flows in the surrounding tissues when the human metabolism becomes active. This study attempted to measure hemodynamic response changes in the main olfactory bulb (MOB) of rats when they are stimulated with odorants, using Imagent equipment in the frequency domain type. In order to measure hemodynamic changes, wavelengths around 800 nm, where the absorbencies of HbO₂ and Hbr become equal, were selected. In addition, 690 nm and 830 nm laser diodes were used in the Imagent system and optical coefficients were derived from the changes in the signal intensities of phase and light. Using the optical coefficients derived, odorants were reversely inferred from the hemodynamic changes in the MOB of rats when they were stimulated by odorants. This study performed an analysis on how concentration changes in the MOB of rats, according to odor stimulations, and their variations, according to the lapse of time, influence the reverse inference of odorants. When analyzing the concentration changes in the MOB of rats, this study used only the information of HbO₂.