Information entropy-based estimation of hand and elbow movements using ECoG signals

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Abstract: 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 show that the performance averages 74% when the ECoG of γ band is used, which is higher than that when other bands are used, and higher estimation success rates are shown in the γ band than in other bands. The time of the movements is divided into three time sections based on movement time points, and the "Before" section, which includes the readiness potential, is compared with the "Onset" section. In the "Before" section and the "Onset" section, estimation success rates are 66% and 65%, respectively, and thus it is determined that the readiness potential could can be used.

Key words: electrocorticogram(ECoG); γ band; entropy; maximum likelihood estimation; readiness potential

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0 Introduction

The brain-computer interface (BCI) is a study area for interactions between the brain and the computer. Since it is controlled by using the brain's electrical activities, it 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 resolution and signal-to-noise ratios (SNR).

Recently, in the study of ECoG data-based BCI, the estimation of actual movements or imaginations of movements are conducted. At College of Education of Beijing Normal University, the movements of the ring finger of the left hand and the tongue are 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. Dr. 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

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power of certain bands were also conducted. Brainwaves can be divided into five bands: 0 − 3 Hz (δ), 4 − 7 Hz (θ), 8 − 13 Hz (α), 14 − 30 Hz (β) and 31 − 100 Hz (γ). In particular, studies on emotions and behavior using γ band have been conducted frequently[2]. One study indicated that the power of ECoG signals generated because behavior increases in γ 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 is divided into three sections based on movement time points, and the characteristics of the signals are extracted using information entropy. The three sections includes a section in which the readiness potential (used to reduce system delays) is observed. Based on the movement time points, the section from −0.75 s to −0.25 s is set as the "Before2", the section from −0.5 s to +0 s as the "Before1", and the section from −0.25 s to +0.25 s as the "Onset", and the lengths of all the sections are the same at 0.5 s. Probabilistic models are made based on the statistical characteristics of the information entropy obtained from each section, and actual movements are estimated using the maximum likelihood estimation method.

In this paper, section 1 describes the methods used to obtain ECoG signals and methods used to process the signals, and section 2 describes the experimental results. Finally, section 3 draws a conclusions.

1 Methods

1.1 Signal acquisition

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 about 10 min.

1.2 Entropy-based ECoG signal model

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, as shown in Fig. 1.

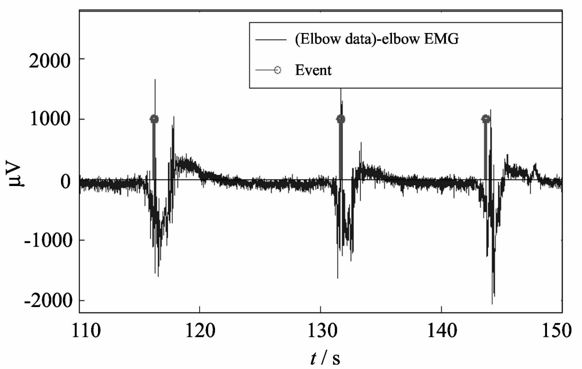


Fig. 1 Elbow surface EMG and event-detection results

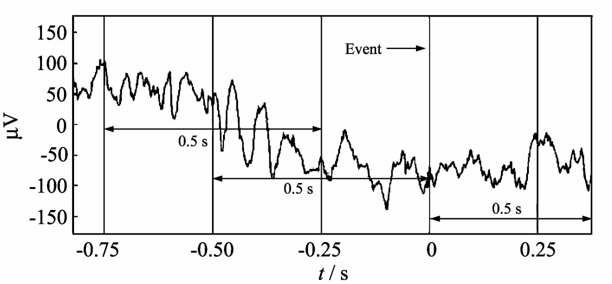


Fig. 2 "Before2", "Before1", Onset" setting method

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 mindicates 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

$$H(X) = -\sum_{k=1}^{K} p(x_k)\log_2 p(x_k), \tag{1}$$

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

$$0 \leqslant p(x_k) \leqslant 1, \tag{2}$$

$$\sum_{k=1}^{K} p(x_k) = 1. \tag{3}$$

Probability $p(x_k)$ can be calculated by

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

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

$$k = 1, 2, \cdots, K, \tag{4}$$

where K determines the number of range I_k by which the samples of $x_{c,m}[n]$ are divided and M is calculated by

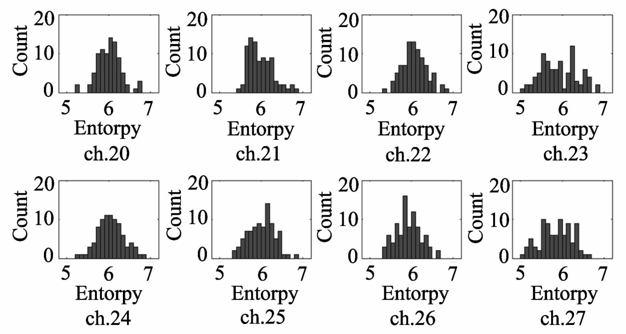
$$M = \frac{(x_{\max} - x_{\min})}{K}, \tag{5}$$

where $x_{\max}$ 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

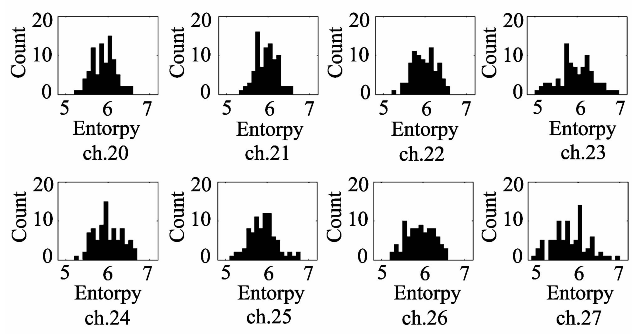
$$H_{c,m} = -\sum_{k=1}^{K} p_{c,m}(x_k)\log_2 p_{c,m}(x_k). \tag{6}$$

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 cth channel of movement m was obtained and compared.



(a) ECoG signals corresponding to subject B's elbow movements were used



(b) ECoG signals corresponding to subject B's hand movements were used

Fig. 3 Example histograms of each behavior

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.

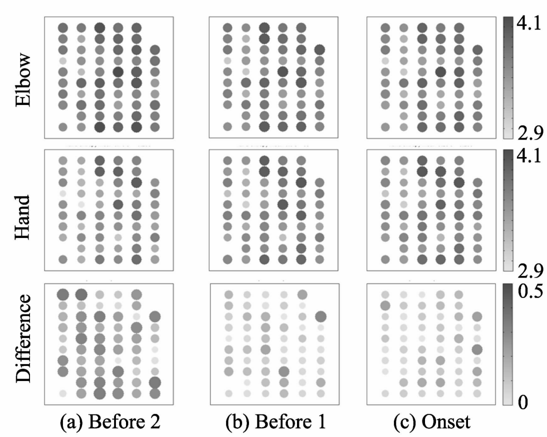


Fig. 4 Average of entropy in the full band of subject B's ECoG signals

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

$$f_{c,m}(t) = \frac{1}{\sqrt{2\pi(\sigma^2)_{c,m}}}\exp\left[-\frac{(t-\mu_{c,m})^2}{2(\sigma^2)_{c,m}}\right],$$

$$\mu_{c,m} = \frac{1}{L}\sum_{l=1}^{L} H^l_{c,m},$$

$$\sigma^2_{c,m} = \frac{1}{L}\sum_{l=1}^{L}(\mu_{c,m} - H^l_{c,m})^2. \quad (7)$$

1.3 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

$$\hat{m} = \arg\max_m\left(\prod_{c=1}^{ch} f_{c,m}(t \mid m)\right) = \arg\max_m\left(\sum_{c=1}^{ch}\log(f_{c,m}(t \mid m))\right), \quad (8)$$

where ch is the number og ECoG channels. By taking logarithms of both sides, the multiplications can be changed into sums and the value of m that maximizes the likelihood; $\hat{m}$ represents estimated movements and compares likelihood in the entropy-based ECoG signal model to find movements that yield the maximum value.

2 Experimental 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 δ, θ, α, β and γ 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 γ 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. In γ band, subject A 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.

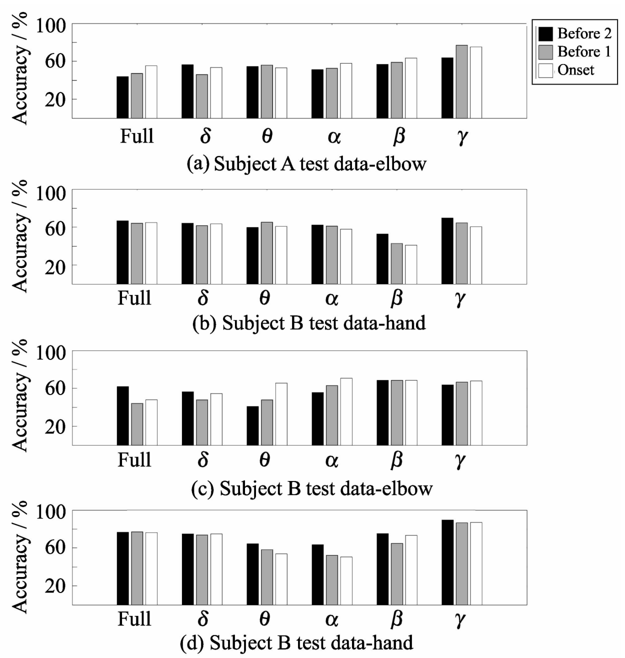


Fig. 5 Estimation success rates for the movements of subjects A and B

3 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

[1] Ince N F, Goksu F, Tewfik A H. An ECoG based brain computer interface with spatially adapted time frequency patterns. International Conference on Bio-inspired Systems and Signal Processing, Portugal, 2008.

[2] Miller K J, Shenoy P, den Nijs M, et al. Beyond the gamma band: the role of high-frequency features in movement classification. IEEE Trans. on Biomedical Engineering, 2008, 55:1634-1637.

[3] YUAN Yuan, XU An-bang, GUO Ping, et al. ECoG analysis with affinity propagation algorithm. Proc. of the 4th International Conference on Natural Computation, 2008, 5: 52-56.

[4] LI Ming-ai, YANG Jin-fu, HAO Dong-mei, et al. ECoG recognition of motor imagery based on SVM ensemble. Proc. of 2009 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2009: 1967-1972.

[5] ZHAO Hai-bin, YU Chun-yang, LIU Chong, et al. ECoG-based brain-computer interface using relative wavelet energy and probabilistic neural network. Proc. of the 3rd International Conference on Biomedical Engineering and Informatics(BMEI), 2010, 2: 873-877.

[6] Crone N E, Miglioretti D L, Gordon B, et al. Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. II. Event-related synchronization in the gamma band. Oxford: Brain, 1998, 121: 2301-2315.

[7] Menon V, Freeman W J, Cutillo B A, et al. Spatio-temporal correlations in human gamma bands. Electroencephalography and Clinical Neurophysiology, 1996, 98: 89-102.

[8] You K J, Shin H C. Classifying finger flexing motions with surface EMG using entropy and the maximum likelihood method. The Institute Of Electronics Engineers of Korea, 2009, SC:(6):38-43.

[9] Bercher J F, Vignat C. Estimating the entropy of a signal with applications. IEEE Trans. on Signal Processing, 2000, 48(6): 1678-1694.