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An improvement of a time-frequency approach for an EEG-based brain-computer interface

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***Abstract* – We have improved upon a Time-Frequency approach of classification of motor imagery (MI) tasks for brain-computer interface (BCI) applications. Through off-line data analysis on data collected during a "cursor control" experiment, we evaluated the capability of our improved method in revealing the major features of the EEG control and enhancing MI classification accuracy. The pilot results in a human subject are promising, with an accuracy rate of 92.1.**

I. INTRODUCTION

The ultimate goal of brain-computer interface (BCI) techniques shall be to provide those people with severe motor disabilities alternative means of communication and control [1]. Typically, an EEG-based BCI system extracts, from scalp-recorded EEG, features encoding human intention and conveys the resulting control signals to the external world. One type of brain-computer interfaces is based on the detection and classification of the change of EEG rhythms during different motor imagery (MI) tasks, such as the imagination of left- and right-hand movements. The accuracy of MI classification directly determines the performance and reliability of such BCI applications, and thus is of importance. Recently, we have developed a new approach in our laboratory for motor imagery classification by means of a weighted time-frequency scheme in an attempt to define a novel and improved EEG-based BCI [2-3]. Furthermore, we have proposed a time-frequency approach [4] and evaluated its capability in enhancing the accuracy of motor imagery classification in comparison with the online performance using BCI2000 [5].

In the present study, we propose a new time-frequency approach to enhance the performance of BCI.

II. METHODS

A. Data description

The scalp EEG signals were recorded from 32 electrodes, placed over the upper hemisphere with a sampling rate of 200Hz, during an online cursor control experiment utilizing the BCI2000 – a general-purpose system for BCI research [5]. Specifically, a subject sat at a monitor and watched a cursor move continuously from left to right across the screen. A vertical target bar randomly appeared near either the upper-right corner or the lower-right corner. The subject attempted to deflect the cursor up or down to hit the bar by imagining left- or right-hand movement, which was accomplished by an online BCI process that responded to subject's intention based on *mu* rhythm (8-12Hz) features [5,6]. Nine electrodes over the somato-sensory cortex (the primary cortical region related with motor-imagery neural activity) were selected from the 32 electrodes for off-line data analysis. The off-line data analysis on a subject (a 23 year old female) is presented in this paper.

Each trial began with a 1 second period in which the target appeared on the screen without the cursor. During the subsequent 4 seconds, the cursor appeared and moved across the screen, with the subject performing the left- or right-hand motor imagery task. The next 1 second time interval consisted of both the cursor and the target remaining on the screen if the subject successfully 'hit' the target else, in the case of a 'miss', the cursor remained and the target disappeared. The final 1 second interval consisted of a blank screen.

The subject completed 480 trials evenly divided between left- and right-hand imagination. The experiment was carried out twice a week for a minimum of three weeks.

B. Preprocessing

During the off-line data analysis, the recorded EEG signals were sequentially preprocessed by applying surface Laplacian filtering, frequency decomposition and ERD/ERS feature extraction.

Scalp recorded EEG represents the noisy spatial overlap of activities arising from very diverse brain regions. Surface Laplacian filtering attempts to accentuate localized activity and reduce diffusion in multi-channel EEG. Assuming that the distances from a given electrode to its four directional neighboring electrodes are approximately equal, the surface Laplacian can be approximated by subtracting the average value of the neighboring channels from the channel of interest as Eq(1).

$$V_j^{Lap} = V_j - \frac{1}{n}\sum_{k\in S_j} V_k \qquad (1)$$

where V_j is the scalp potential EEG of the jth channel, and S_j is an index set of the four neighboring channels.

The EEG component from 6 to 30 Hz was further decomposed into multiple frequency bands using a constant-Q (also called proportional-bandwidth) scheme [2]. Specifically, we constructed a set of fourth order Butterworth band-pass filters, each of which span the indicated octaves with the ratio (Q) of the center frequency to the bandwidth being chosen to be a constant. The neighboring frequency bands had certain overlapping to allow a proper redundancy of signals.

We delineated the event-related desynchronization (ERD) and the event-related synchronization (ERS) features [7] within each frequency band by extracting the envelope of instantaneous powers of decomposed signals [2]. The ERD/ERS features were further simplified by down-sampling the envelope, since the high frequency (>5Hz) component can be ignored for most envelopes (Details see [2]).

C. Classification by correlation of spatiotemporal patterns

Signals from 9 electrodes were used in the classification. Each signal was decomposed into 13 frequency bands and 13 envelopes were extracted from the 13 decomposed signals, i.e. a spatiotemporal pattern of a trial was composed of 117 envelopes. The 117 envelope vectors were connected in order of electrode, i.e. F3, F4, Fz, C3, C4, Cz, P3, P4, Pz, and the 13 envelope vectors of each electrode vector were connected in order of frequency, to be a row vector. The row vector was represented as p. Two types of averaging vectors, P_L and P_R, were made using training data to calculate the correlation, where the subscript L or R stood for the tasks of left or right-hand imagined movements. Correlation coefficients $C = C(p,P)$ were calculated using (2).

$$C = \frac{(p-\overline{p})^T (P-\overline{P})}{\left\|p-\overline{p}\right\| \bullet \left\|P-\overline{P}\right\|} \tag{2}$$

Where $\overline{p}$ and $\overline{P}$ denote the mean values of p and P respectively.

D. Method-I: Classification by correlation of comprehensive vectors with time-frequency spatial information

We introduced a comprehensive vector with time-frequency spatial information. The algorithm of this method is as follows. First, the same P_L and P_R vectors in section C are made, and the values of the correlation coefficients between two envelopes with the same electrode and the same frequency consisting of P_L and P_R are calculated. When the values are larger than a threshold C_0, the corresponding envelope data are deleted from both P_L and P_R. The value of C_0 is determined to give good classification accuracy in the training data. ****** Next, the remaining envelope vectors are connected to be a row vector for P_L and P_R, and the two reconstructed vectors are denoted $P_{c,L}$ and $P_{c,R}$ respectively. The test vectors, p_c, are constructed using its envelope data that are the same frequency and electrode as P_L and P_R. The classification of left or right is determined by the value derived from (3), i.e. d_I=1 and -1 denote left and right respectively.

$$d_I = \mathrm{sgn}\left[C(p_c, P_{c,L}) - C(p_c, P_{c,R})\right] \tag{3}$$

E. Method-II: Classification method using envelopes of the decomposed EEG signals in *mu* and *beta* frequency bands

The amplitudes of the envelopes in *mu* (8–12 Hz) and *beta* (13–28 Hz) frequency bands change according to hand movement. This feature is used in method-II to infer left or right hand that the subject imagined. At first, two signals that reflect the hand movement best are detected. Those were the signals recorded from electrode P3 and P4 for this subject. The basic algorithm of this method is a comparison of the integration value of the two signals. Generally, there is individual difference in the frequency band reflecting the hand movement. Therefore, proper frequency bands of envelopes are detected. In the present study, the values of center frequencies of the bands were about 9, 10, 12, 13, 15, 18 and 20 Hz. Furthermore, in order to remove an influence of background EEG that prevents the inference of imagined hand, a threshold value is set to the amplitude of the envelopes for the integration in case of necessity. These values are determined using training data set. The values of integration were calculated using (4) and (5).

$$I_{P3} = \sum_{m \in F} \int_0^5 v_m^{P3}(t)dt \tag{4}$$

$$I_{P4} = \sum_{m \in F} \int_0^5 v_m^{P4}(t)dt \tag{5}$$

where $v_m^{P3}(t)$ and $v_m^{P4}(t)$ are envelopes of center frequency m, and F is an index set of the center frequencies.

$$d_{II} = \mathrm{sgn}\left[I_{P4} - I_{P3}\right] \tag{6}$$

The classification of left or right is determined by the value derived from (6), i.e. d_{II}=1 and -1 denote left and right respectively.

F. Method-III: Classification method using method-I and II.

There were several trials for which method-II returned more accurate results than method-I. However, there were also several cases to the contrary. In method-III a trial was first inferred by method-I. Next, the result was reexamined using method-II. In the reexamination, six threshold values were used to adopt the result of method-I or II. Three values (I_L, C_{LL} and C_{RL}) were used for the trial to infer imagination of left hand movement. The other three values (I_R, C_{LR} and C_{RR}) were used for the trial to infer imagination of right hand movement. In the reexamination procedure, only the trials in which methods I and II differed in result were reexamined. For trials that were reexamined, the three values of I_{P4}-I_{P3}, $C(p_c, P_{c,L})$ and $C(p_c, P_{c,R})$ were compared with three corresponding threshold values. For example, for the trial that inferred imagination of left hand movement, the values of I_{P4}-I_{P3}, $C(p_c, P_{c,L})$ and $C(p_c, P_{c,R})$ were compared with those of I_L, C_{LL} and C_{RL}, respectively. The six threshold values were determined to correct the incorrect inference results from the training data set.

III. Results

The classification accuracy rates were calculated using the three aforementioned methods and the results are shown in Table I. The values in the parenthesis of the columns are the value of threshold C_0. The rates calculated by method-I, II and III are compared with that of BCI2000. As can be seen in Table I, method-III has enhanced accuracy rate compared to method-I.

TABLE I
ACCURACY RATES [%] OF 1 SUBJECT

BCI2000	Method-I	Method-II	Method-III
83.3	90.8	85.0	92.1

IV. Discussion

The present study suggests a method to improve the time-frequency approach for an EEG-based Brain-Computer Interface. Improving the approach, we can further enhance the performance of the BCI. Our pilot study in a human subject indicates an increase in the classification rate from 90.8% (previous time-frequency approach) to 92.1%. Overall, the performance was enhanced from 83.1% (BCI2000) to 92.1%. An additional advantage of the previous time-frequency approach, the short calculation time (about 0.3sec/trial), is preserved with this new method. Therefore, the present method is suitable for implementation in on-line experiments. In summary, this pilot study is promising and suggests the time-frequency approach merits further investigation to enhance the classification accuracy of EEG-based BCI systems.

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