Classification of Finger Pairs from One Hand Based on Spectral Features in Human EEG*

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***Abstract*— Individual finger movements are well-articulated movements of fine body parts, the successful decoding of which can provide extra degrees of freedom to drive brain computer interface (BCI) applications. Past studies present some unique features revealed from spectral principal component analysis (PCA) on electrophysiological data recorded in both the surface of the brain (electrocorticography, ECoG) and the scalp (electroencephalography, EEG). These features contain discriminable information about fine individual finger movements from one hand. However, the efficacy of these spectral features has not been well investigated under the application of various classifiers. In the present study, we set out to investigate the topic using noninvasive human EEG. Several classifiers were chosen to explore their capability in capturing the spectral PC features to decode individual finger movements pairwisely from one hand using noninvasive EEG, aiming to investigate the efficacy of these spectral features in a decoding task.**

I. Introduction

Brain-computer interface (BCI) is a fast growing field in the community of biomedical research. Its systems translate neurophysiological signals of the human brain into control commands for peripheral devices, aiming to assist people with severe motor disabilities [1], [2]. Different functional modalities of the human brain have been implemented for BCI, such as sensorimotor rhythm (SMR) during real movements or motor imagery [3], [4], attention-induced P300 [5], and steady state visual evoked potentials (SSVEP) [6].

Among these patterns, SMR gains more interests in BCI [7], [8], [9] due to the reason, unlike the other two, that it can be evoked without external stimuli. This property of SMR opens up the restriction of BCI applications, and offers better volitional control experience for BCI users. However, SMR-based BCIs suffer from limited degrees of freedom (DOFs), i.e., the small number of reliable control signals available, which significantly constrains the complexity of BCI applications.

Individual finger movements are well-articulated movements of fine body parts, the successful decoding of which can provide extra DOF of control signals to drive BCI applications. Previous study has showed that spectral features extracted from spectral principal component analysis (PCA) contain discriminative information about different finger movements in electrocorticography (ECoG) [10]. Another study found such features in scalp electroencephalography (EEG) as well, advancing the application of individual finger movements towards noninvasive BCI applications [11]. However, the efficacy of spectral features from PCA has not been well studies through the selection of different classifiers, which is a necessary step when integrating with real-life applications.

Several popular and representative classifiers based on either generative or discriminative models could serve the purpose of evaluation, including linear discriminant analysis (LDA) classifier [12], quadratic discriminant analysis (QDA) classifier [13] and support vector machine (SVM) classifier [14]. Among these classifiers, both LDA and QDA find a decision boundary to separate different classes. While LDA assumes equal covariance matrix for two classes, QDA ease up on such a requirement, allowing different Gaussian distributions for different classes. The SVM classifier relies further on data, by finding a hyper plane, on which the boundaries of projections from different classes can be maximally separated.

In the present study, we set out to investigate the efficacy of spectral features from PCA decomposition by implementing three representative classifiers in decoding pairwise finger movements from one hand using noninvasive EEG. The achieved results could help further understanding these spectral features, as well as providing some reference for the selection of classifiers for decoding individual finger movements in future noninvasive BCI applications.

II. Methods

A. Experimental Data

EEG data were recorded from six subjects, one female and five males. All subjects are right handed, with mean age of 27.3. All of them have given informed consents. Data from five of them were utilized for analysis, with one excluded due to noise. Experiments were carried out in a specialized chamber room to shield electromagnetic noise from surround environment. The EGI's Geodesic EEG System 300 (GES 300) was used with a 128-electrode HydroCel Geodesic Sensor Net (HCGSN) to record EEG signals at a sampling frequency of 1000 Hz. At the same time, potential differences caused by finger movements were captured using five bipolar sensors attached to the front and back of each finger. Examples of potential differences were shown in Fig. 1(a).

During the experiments, subjects were instructed only to move according to cue words and avoid other movements.

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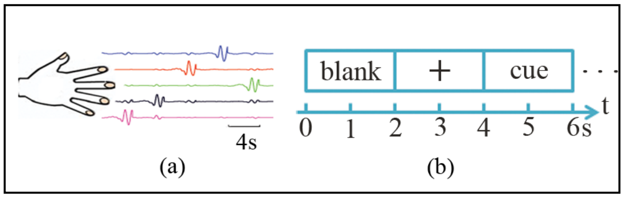

Figure 1. Experimental Design. (a) Potential differences caused by finger movements. (b) Each trial protocol.

The cues were presented using E-Prime software and designed as shown in Fig. 1(b). Each trial lasted 6 seconds. For the first 2 seconds, the screen was blank and subjects could blink their eyes or swallow if needed. During the next 2 seconds, a fixation cross was shown at the center of screen. Subjects were instructed to stare at the cross without any movements. This duration served as resting condition in the following data analysis. In the last 2 seconds, one of five words (i.e., thumb, index, middle, ring, and little) was randomly selected and displayed on the LCD screen. Continous finger movements were required during this period, and subjects usually were able to move the corresponding finger twice in each trial. There were either 60 or 80 trials for each finger condition, resulting in 300 or 400 trials in total.

B. Preprocessing

Raw EEG data usually contain artifacts, such as environmental noise picked up by EEG sensors, and motion artifacts generated from unwanted movements of subjects. A serial of preprocessing steps were applied onto raw EEG to increase the signal-to-noise ratio (SNR) of EEG. Firstly, a 0.3 Hz high-pass IIR filter was implemented to remove DC drifting, followed by a 60 Hz notch filter to reduce influence from power lines. Secondly, EEG channels with kurtosis values larger than 5 were marked as bad channels and rejected using EEGLAB toolbox [15]. Their values were then filled by interpolation from average EEG readings of surrounding channels. Thirdly, with values from all channels fixed, a spatial filter named common average reference (CAR) was implemented to further increase SNR of EEG [16]. It calculated the average potential across all channels for each time point, and used it to re-reference EEG from each channel. Since common artifacts were usually consistent across all channels, they could be removed in such a manner. In the last step of preprocessing, independent component analysis (ICA) from the EEGLAB toolbox was performed [15]. There were 64 independent components (ICs) decomposed from the original datasets, which represented different brain functional substrates. Each IC pattern was inspected, and those associated with EEG artifacts were rejected. After artifact rejection, data were projected back to electrode domain from IC domain.

TABLE I. EXPERIMENTAL TRIALS

Subject	Number of Movement Trials				
	Thumb	***Index***	***Middle***	***Ring***	***Little***
1	93	79	80	78	79
2	87	97	117	97	87
3	74	59	84	81	82
4	83	77	86	80	109
5	68	105	88	71	64

Simple preprocessing steps were also applied to potential differences from bipolar sensors, including band-pass filter from 0.5 to 2 Hz to capture the frequency of subjects' finger movements. Following preprocessing procedures, movement peaks were selected by criteria taking both amplitude and latency of potential differences into consideration (refer to [11] for detail). Based on these movement peaks, 1-second movement segments of EEG were selected for each finger condition. Their corresponding trials of resting condition were defined as 1-second segments in middle of the 2-second fixation period right before finger movements. Detail information about number of trials for each finger condition and each subject is listed in Table I.

C. Spectral Principal Component Analysis

The purpose of spectral PCA was to reveal underlining common spectral features across different finger conditions. The 1-second trials from movement and resting conditions were transferred into frequency domain by calculating the power spectral density (PSD) using a Hanning window. The covariance matrix of spectral powers was then constructed, as the first step of the spectral PCA decomposition. The values on main diagonal of the matrix represent variance on each frequency under different conditions, while the off-diagonal values reveal inter-frequency variation. Following that, eigenvalues and eigenvectors of the covariance matrix were calculated. The eigenvectors were sorted by magnitudes of corresponding eigenvalues from the large to small. These eigenvectors were decomposed spectral principal components (PCs), which account for different variance in EEG data grouped from different conditions in descending order. Finally, spectral data from individual trials of different conditions were projected onto each PC to acquire projections on the obtained new coordinates in spectral structures. The whole procedure was performed on EEG from one channel to another for all channels. See details in [11].

D. Classification and Verification

Before the exploration of different classification techniques for the decoding task, two aspects of the spectral PCA features need to be fixed. First of all, combination of projections from the first three PCs were used for classification, because they account for most variations in EEG data, and our previous study has demonstrated that the existence of discriminative information about different finger movements on these PCs. The second one is the selection of EEG channels to feed into classifiers. The 128 EEG channels span across all brain regions, of which only a fraction contains information related to finger movements. To pin down those channels that are most informative about different finger movements, the coefficient of determination r^2 was calculated [17] using

$$r^2 = \frac{(\mu_1 - \mu_2)^2}{\sigma_{12}} \times \frac{n_1 \times n_2}{n_{12}^{\;2}} \quad . \tag{1}$$

In the equation, μ_1 and μ_2 are means of trials from two conditions of finger movements to be compared, and σ_{12} is standard deviation of the joint data. The symbols n_1, n_2 and n_{12}

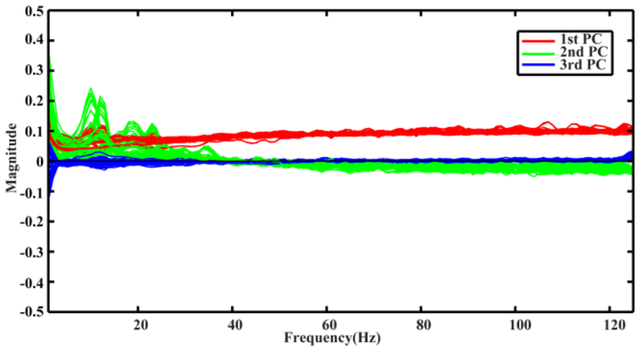

Figure 2. Profiles of the first 3 PCs. Each line represents PC from one pair of fingers from one subject

are constants, denoting the number of trials from each condition and the joint data, respectively. They were introduced in the equation to compensate the effect from unbalanced trial numbers of each condition. Only channels at brain regions associated with motor functions were taken into consideration and rearranged by their corresponding r^2 values. Finally, a universal 50-channel set, that combined top channels for each pair of fingers and covered motor, frontal and parietal cortices, was chosen for decoding pairs of finger movements.

With decoding features selected, we evaluated their decoding efficacy using both generative and discriminative model based classifiers, including LDA, QDA, and SVM. All trials were firstly randomly permuted 20 times to acquire statistical decoding accuracies. The feature selection steps mentioned above were only performed within each permutation to avoid double dipping issue. Under each permutation, classification using different classifiers was proceeded. To compare decoding performance from three classifiers, the Student's t tests were conducted between the decoding accuracies of different pairs of classifiers.

Decoding efficacy of extracted features using different classifiers was also evaluated, by comparing to the guessing level. The general guessing level for a two-class classification problem is 50%, but it only holds for extremely large number of samples. In current study, the empirical guessing level was used for better evaluation. To achieve the empirical guessing level, trials from different conditions were mixed together with their class labels randomly permuted 500 times, and classification was performed within each permutation to acquire the mean decoding accuracy. Then, one-sample Student t-test was performed between decoding accuracy from each classifier and the guessing level.

III. Experimental Results

A. PC Features

Fig. 2 presents the profiles of the first three PCs, which show different magnitudes along frequencies. The first PCs (as depicted by red lines) from all ten pairs of fingers reveal a broadband pattern, generally flat across all frequency bands. The second PCs (as depicted by green lines) mainly peak at alpha and beta bands. The power changes on these frequency bands define the mu rhythm phenomenon, which is the main

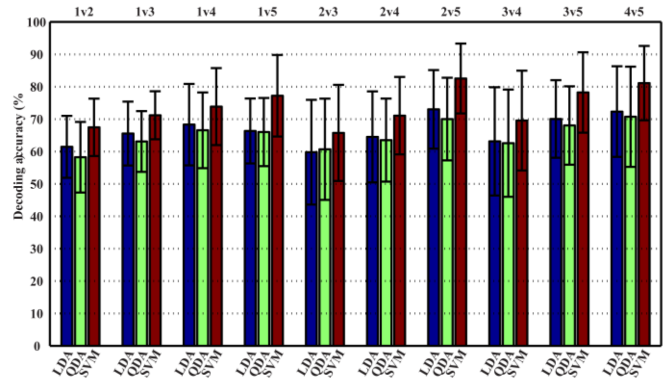

Figure 3. Decoding accuracies using different classifiers for each pair of finger movements. 1: thumb, 2: index, 3: middle, 4: ring, 5: little.

composition forming the profiles of second PCs. The third PCs (as depicted by blue lines) are with small magnitudes around zero with very little variation. These profiles revealed by spectral PCA decomposition in noninvasive EEG match the description of those found in ECoG [10], indicating the strong existence of such features in human EEG from both invasive and noninvasive measurements.

B. Decoding Accuracies

Fig. 3 presents the decoding accuracies for each pair of fingers from three classifiers, using projections on the first three PCs as decoding features. Numbers 1 to 5 on top of the figure denote fingers from thumb to little, respectively. Small variations can be observed for decoding accuracies of difference classifiers on different pair of fingers. The trends are similar for all classifiers. For each pair of fingers, all three classifiers are able to produce decoding accuracies larger than 50%, but to different extents. Two-sample t-tests show that decoding accuracies from LDA are significantly larger than those from QDA for most of finger pairs ($p < 0.05$) except the pairs of thumb-little, index-middle and middle-ring. The decoding accuracies from SVM exceed those from LDA and QDA with significance ($p < 0.05$) for all the pairs.

Fig. 4 presents the empirical guessing level achieved by classifying different pairs of fingers with randomly permuted labels. The average value of the empirical guessing level for all finger pairs is 52.38%. Results of statistical tests between decoding accuracies from different classifiers and the empirical guessing level show that, with the extracted features,

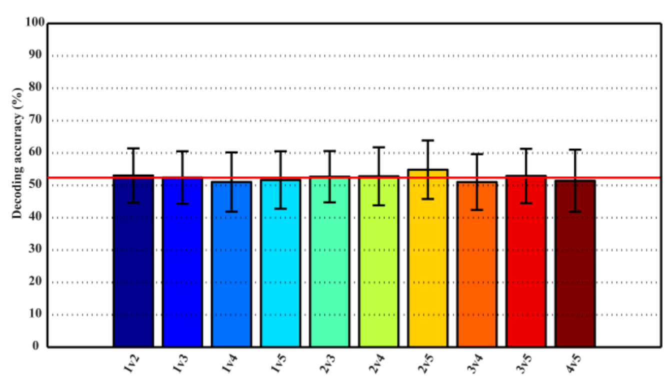

Figure 4. Classification results for each pair of fingers with randomly permuted labels. Red horizontal line depicts the average emperical guessing level.

all three classifiers are able to deliver decoding performance significantly higher than random for all finger pairs ($p < 0.05$). Mean decoding accuracies for LDA, QDA and SVM are 66.45%, 64.95% and 73.80%, and they are all significantly higher than the empirical guessing level as well ($p < 0.05$).

IV. Discussion

In present study, we examined the spectral features revealed from the PCA decomposition, and evaluated their decoding efficacy using different types of classifiers for pairwise decoding of finger movements from one hand. PC features found in noninvasive EEG were similar to those in ECoG. With the PC features, all classifiers were able to produce decoding accuracies significantly higher than the empirical guessing level ($p < 0.05$), but varied in decoding performance, indicating their different abilities to exploit the PC features for the decoding task.

Both LDA and QDA fall into the categories of generative modeling classifiers, which construct the distribution models for both classes and calculate the posterior probability of each class based on Bayes' theorem. Decoding accuracies from LDA were higher than those from QDA for most pairs of finger movements, demonstrating that estimation of identical covariance matrices for different classes could be a better fit for the PCA features than different ones for such classifiers. On the other hand, SVM is one of the classifiers based on discriminative modeling. It converts data from the original domain to a hyper plane, on which the boundaries of different classes can be mostly separated. Significantly higher decoding accuracies achieved by SVM compared to either LDA or QDA ($p < 0.05$) demonstrate that the PC features extracted could be better separated on the hyper plane than manipulations on the original domain, and that discriminative modeling based classifiers might be more suitable to exploit the PC features for the finger decoding task.

Although the extracted PC features yield significant decoding performance than the empirical guessing level in all classifiers tested, the achieved decoding accuracies did not live up to the standard for real-life BCI applications. There could be several aspects to examine for the sake of improving decoding accuracies. Firstly, the current work is preliminary, and more classifiers based on different theories in the machine learning field can be included for evaluation, in search for optimal classifier to accomplish the specific decoding task. Secondly, similar trends of decoding performance on different finger pairs across all three classifiers indicate naïve biology of hands, such as co-activation of adjacent fingers, could affect the decoding performance as well. Therefore, excluding some fingers, that would easily cause confusion or co-activation, from the decoding task may worth exploring in order to improve the overall decoding performance.

To sum up, the present study explored several typical classifiers for decoding pairwise finger movements from one hand using noninvasive EEG, with features extracted from spectral PCA. All classifiers delivered decoding performance with statistical significance, demonstrating the efficacy of spectral PC features in decoding individual finger movements. The SVM type of classifiers shows better ability in capturing the PC features with decoding accuracies surpassing the other two. The results of the present study could speed up the process of utilizing finger movements for BCI control, by exploring different classification techniques for the extracted PC features.

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