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Decoding Individual Finger Movements Using Noninvasive EEG

R. Xiao[1], L. Ding[1,2]

[1]School of Electrical and Computer Engineering, University of Oklahoma;
[2]Center for Biomedical Engineering, University of Oklahoma

Correspondence: Lei Ding, University of Oklahoma, 110 W. Boyd St., DEH room 150, Norman, OK, USA. E-mail: leiding@ou.edu

Abstract. Brain-computer interface (BCI) enables people suffering from severe motor disabilities to control external devices by decoding different patterns of brain activities. One principal challenge, that largely confines the complexity of noninvasive BCI applications, is the limited number of features available to generate control signals. Recent BCI study based on electrocorticography (ECoG) investigated individual finger movements using spectral principal component analysis (PCA). The extracted features demonstrated a great potential in decoding movements of fine body parts, i.e., individual finger movements, which could increase the number of control features for BCI. However, the feasibility of such features in noninvasive BCI has not been tested yet. To advance the development of noninvasive BCI, the aim of the present study is to investigate such spectral features in electroencephalography (EEG). The extracted features were validated by classifying pairwise individual finger movements, resulting in an average decoding accuracy (77.17%) significantly higher than the guess level (50%) in all subjects ($p < 0.05$).

Keywords: BCI, EEG, Individual finger movement, PCA, Noninvasive.

1. Introduction

While EEG has been widely adopted in noninvasive BCI studies [McFarland et al., 2009; Wilson et al., 2009], the limited number of available control features impedes the development of noninvasive BCIs for complex applications [Xiao et al., 2012]. The present study evaluated features about individual finger movements of one hand, which were previously studied using ECoG [Miller et al., 2009], in noninvasive EEG, aiming to advance the development of noninvasive BCI.

2. Material and Methods

2.1. Experimental protocol

During the experiments, subjects performed either rest or repetitive movements of individual fingers from one hand according to visually presented cues. Each trial lasted for six seconds. The first two seconds allowed subjects to rest. The following two seconds provided data for resting conditions with few artifacts by instructing subjects staring at a fixation cross. In the last two seconds, one of five words (thumb, index, middle, ring and little) was randomly presented on the screen, cueing subjects to perform repetitive movements of the corresponding fingers. EEG data were recorded from 128-channel sensor net (Electrical Geodesic Inc., OR, USA) at sampling frequency of 250 Hz. At the same time, bipolar EMG sensors were attached to each finger to detect movement peaks, which were used to extract 1-second segments of EEG data that corresponded to movements in each trial. Data from five subjects were processed and evaluated in the present study.

2.2. Feature extraction and classification

The movement segments as well as resting segments of all trials were referenced to a common average reference (CAR). The EEG temporal potentials were then transferred into spectral powers. Following that, the spectral PCA was performed on data from each pair of fingers. Firstly, the covariance matrix of spectral powers was constructed to reveal inter-frequency correlations and inner-frequency variances produced by trials from different conditions. Secondly, eigenvalues and eigenvectors of the covariance matrix were calculated and arranged according to magnitude of corresponding eigenvalues in a descending order. These eigenvectors were the principal components (PCs) reflecting spectral features related to finger movements. Finally, EEG spectral powers of each trial were projected onto different PCs to acquire projection coefficients, which were features fed to classifiers for decoding.

The support vector machine (SVM) classifier was implemented to classify movements from each pair of fingers using a five-fold cross validation. Eighty percent of trials were used to train parameters for the classifiers, and the rest for testing. Decoding accuracies were achieved by comparing predicted labels from the classifiers to the true labels. The whole process was repeated 20 times with trials randomly permuted to yield mean decoding accuracies.

3. Results

Features from spectral PCA decomposition are consistent across different subjects and permutations (Fig. 1). The first PCs (blue curves) present a broadband pattern, which is flat and with positive magnitudes at all frequencies. This pattern is consistent with the broadband phenomenon reported in the ECoG study [Miller et al., 2009]. The second PCs (red curves) mainly peak at some low frequency bands, including alpha and beta bands, revealing power changes in these frequency bands during individual finger movements. When implementing projection coefficients of different PCs in the classifiers, different optimal decoding accuracies are achieved for different pair of fingers, with index vs. little the highest at 86.11% and thumb vs. index the lowest at 70.98%. The average decoding accuracy across all pairs of fingers is 77.17%, which is significantly higher than the guess level at 50% ($p < 0.05$).

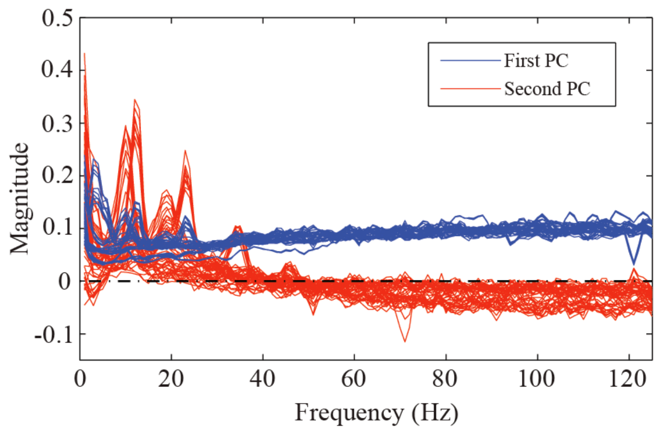

Figure 1. *First and second spectral PCs from 20 permutations and all subjects.*

4. Discussion

With the use of spectral PCA decomposition, the resulting spectral PCs were in line with those in ECoG, suggesting that the spectral features indicative of individual finger movements from one hand exist in EEG as in ECoG. The achieved decoding accuracy further confirmed the validity of such information in EEG. The findings demonstrated that EEG contains useful information to decode individual fingers, which can increase the number of control features for noninvasive BCIs. The present study is promising to advance the development of BCI towards noninvasiveness by transferring features from ECoG to EEG.

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References

McFarland DJ, Sarnacki WA, Wolpaw JR. Electroencephalographic (EEG) control of three-dimensional movement. *J Neural Eng*, 7(3):036007, 2009.

Miller KJ, Zanos S, Fetz EE, den Nijs M, Ojemann JG. Decoupling the cortical power spectrum reveals real-time representation of individual finger movements in humans. *J Neurosci*, 29(10):3132-3137, 2009.

Wilson JA, Schalk G, Walton LM, Williams JC. Using an EEG-based brain-computer interface for virtual cursor movement with BCI2000. *J Vis Exp*, 29:e1319, 2009.

Xiao R, Liao K, Ding L. Discriminating multiple motor imageries of human hands using EEG. In *Proceedings of the 34th Annual International Conference of the IEEE/EMBS*, 1773-1776, 2012