A Study of EEG Features For Multisubject Brain-computer Interface Classification

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BRAIN computer interface (BCI) is a communication technique that aims to detect and identify brain intents and translate them into machine commands to control the operation of electrical and/or mechanical devices. Electroencephalography (EEG) is a widely used imaging technique for noninvasive BCI. Due to EEG non-stationarity, which is typically caused by variation of head size, electrode positions and/or impedance, subjects' mind states, eye or muscular movements, EEG signals exhibit significant inter-subject variation. As a result, a BCI system trained from a subject may not be directly applicable to others, and a significant amount of time is required to re-calibrate the BCI system to a new subject. This inefficiency is one of the major challenges in EEG-based BCI systems. The goal of this work is to address the multisubject BCI classification by evaluating a set of EEG features and identifying those showing higher stationarity than others.

Four EEG datasets from BCI competitions III (datasets IIIa and IVa) and IV (datasets IIa and IIb) were used in the study [1,2]. These datasets were acquired from multiple subjects under motor imagery tasks. There are 60 EEG channels in dataset IIIa, 118 channels in IVa, 22 channels in IIa, and 3 channels in IIb. Two types of features were extracted and investigated using the datasets. The first type of features are directly extracted from the EEG data, including subband power, autoregressive model (ARM) parameters, and the data projection variance extracted after performing the common spatial patterns (CSP)-based spatial filtering [3]. The second type of features were extracted after implementing a 3-scale wavelet transform on the EEG data. The stationary wavelet transform (SWT) was used to calculate approximation and detail coefficients of the EEG data [4]. SWT is translational invariant and helpful to identify stationary information across different subjects. Subband power and ARM parameters were computed from approximation and detail coefficients at each wavelet scale. Combinations of these features from multiple scales were also evaluated. The experimental study was performed based upon a challenge setting: a linear support vector machine (SVM) was trained using features extracted from training data of an individual subject in a dataset, and used to classify testing data from all other subjects in the same dataset. A cross validation was performed so that features computed from each subject's training data were used once to train the SVM to classify all other subjects' testing data. The classification accuracy was calculated based upon the cross validation results. To minimize the contribution from other data processing steps, the EEG data were minimally preprocessed with a 8-32 Hz band-pass filtering. Eye movement artifacts in datasets IIa and IIb were attenuated using regression based on the simultaneously acquired electrooculogram data [5]. The experimental results show that when the first type of features were used, the ARM parameters or CSP projection variance provided the lowest accuracies ranging from 50.28% to 56.27%. The subband power led to a 1.03%~4.13% increase in accuracy as compared to those obtained using the ARM or CSP features. When the second type of features were used, further increases in accuracy ranging from 1.1% to 9.57% were achieved, and the subband power outperforms the ARM parameters with increases ranging from 1.27% to 13.44%. These results indicate that the subband power features are relative more robust than the others for the multisubject BCI classification. In addition, the features calculated from SWT may better characterize stationary information across different subjects. It was also observed that a combination of features from multiple wavelet scales does not perform better than features from a low wavelet scale. This is reasonable because higher wavelet scales would introduce high frequency information that is subject-specific and can deteriorate the multisubject classification performance.

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