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BCI oriented EEG analysis using log energy entropy of wavelet packets

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ABSTRACT

Brain computer interfacing (BCI) is the practice of establishing a direct communication between a human and a computer by self-regulation of some electrical activity in the brain. Electroencephalography (EEG) based BCI is one of the most promising form of this application where a subject learns to control brain waves of type μ-rhythm (8–14 Hz) or β-rhythm (14–30 Hz) or P300 event related potential or slow cortical potentials (SCPs). Intents of the person is extracted using signal processing techniques. In this study self-regulation of SCPs is studied using wavelet packet analysis (WPA), rather than traditional time or frequency domain methods. WPA, by providing arbitrary time-frequency resolution, enables analyzing signals of stationary and non-stationary nature. It has better time representation than Fourier analysis and better high frequency resolution than Wavelet analysis. WPA subimages are analyzed further by log energy entropy. These feature vectors are fed into a multilayer perceptron (MLP) for classification. We use the BCI Competition 2003 datasets Ia and Ib to test our approach. Performance of the MLP is compared with that of k-NN and SVM. Our method achieves accuracies of 92.8% and 63.3% on datasets Ia and Ib respectively. This outperforms the other reported results on the same datasets including the winners of the competition. Overall, WPA followed by Log Energy Entropy and MLP provides an efficient tool for the aforementioned kind of BCI oriented EEG analysis.

1. Introduction

Self-regulation of the brain wave rhythms constitute the basis of electroencephalographic (EEG) brain computer interfacing (BCI). This establishes a direct communication between the brain and a computer which can be used in assisting the disabled in communication with a computer or providing an alternative control method for powered prosthesis or a new way of neuro-rehabilitation. In this kind of practice, certain aspects of electrical signals from the brain are analyzed and the results of that analysis is presented to the subject in visual or audial form so that he/she can learn to control the signals by thinking, for example, by imagining doing a task. During the process, brain waves, especially in the frequency ranges: μ-rhythm (8–14 Hz) or β-rhythm (14–30 Hz) or P300 event related potential or slow cortical potentials (SCPs) change.

SCPs, which are an important part of BCI applications, are the positive or negative DC deflections in the EEG signals which can be observed in some cognitive tasks such as language and sensory motor tasks in the form of motor preparation and expectation. They have uses in psychophysics, BCI and neuro-feedback rehabilitation [2,4]. SCPs are also shown to encode parameters that belong to real or imagined limb movements [5,6] and to have impairment related information in movement related EEG activity in stroke patients [8], which shows its potential in diagnosis and prognosis as well.

In BCI related EEG analysis, many different signal processing techniques have been used in the literature. Time domain, frequency domain (Fourier) and time-frequency domain (Wavelet) analysis are the main tools used for these analysis, but while Fourier analysis has poor time representation, wavelet analysis has poor resolution at high frequency. Wavelet Packet Analysis (WPA), on the other hand, overcomes both of these, and the arbitrary time-frequency resolution enables analysis of signals of both stationary and non-stationary nature [16].

In BCI related EEG analysis applications, WPA has been used. For example, Banghua et al. [11] used common spatial pattern (CSP) of WPA to form features to be classified by a probabilistic neural network (PNN). They tested their method on 2008 BCI competition dataset and their laboratory experimental data. They achieved classification accuracies of 92% and 80% for two datasets. Another application was by Yang et al. [12], who adapted fisher Wavelet Packet Decomposition (WPD) CSP to each subject separately. They firstly decomposed EEG channels by WPA. Then they calculated average power values for each subband. Afterwards, they selected specified subbands with larger fisher distance and reconstructed each subband which were input to CSP. This feature is then classified by a PNN. They tested the method using six subjects and discovered that subject specific WPD-CSP showed up to 14%

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improvement compared to nonsubject-based fisher WPA-CSP. The dataset they used was from their own laboratory experiments of left or right hand movement imagination. Two more applications of WPA was done: Yang et al. [13] used WPA-CSP followed by Kernel Fisher Support Vector Machine (KFSVM) for EEG recognition in motor imagery BCI. They tested their method on the 2008 international BCI competition and showed that their method improves EEG recognition accuracy in motor imagery BCIs. The second application was by Kevric and Subasi [14], who compared empirical mode decomposition, discrete wavelet transform and WPA in terms of their accuracy in a multichannel 2-class motor imagery dataset, the BCI Competition III dataset IVa. They showed that multiscale principal component analysis used for noise removal followed by higher order statistics features including mean, average power, standard deviation, ratio of the absolute mean values, skewness and Kurtosis of the coefficients from WPA provided the highest classification accuracy of 92.8%.

Several other authors used WPA in BCI related EEG analysis applied in self-regulation of SCPs. For this purpose, these authors used BCI Competition 2003 datasets Ia and Ib. The first application was by Wang et al. [19] who combined SCPs and the specific energy from the time-frequency domain from the beta band via WPA. They used 3-layer perceptron and SVM for classification. In their testing of the method on BCI Competition 2003 dataset Ia, they achieved 91.47% accuracy with the perceptron neural network classification. Second result was by Ting et al. [10] who combined average of coefficients with sub-band energy of WPA and applied Fisher distance criterion to select most relevant features. They applied their method to BCI Competition 2003 datasets Ia and Ib and achieved 90.8% and 59.1% accuracies respectively. Another application was by Hu et al. [21] who used coefficients means of WPD along with wavelet packet energy which were reduced using Fisher discriminant analysis. They applied their method to BCI Competition 2003 dataset Ia and achieved 90.1% accuracy. The last example in this line is by Hettiarachchi et al. [9] who extracted subband energy and subband coefficient average of the WPD as initial features. They selected part of these initial features using Receiver Operating Characteristic (ROC) and compared this with selection by Fisher Distance Criterion (FDC). They tested their method on BCI Competition 2003 Dataset Ib and achieved better accuracy of 59.44% using ROC feature selection.

In the aforementioned applications we see that there was extensive use of WPA on datasets Ia and Ib of BCI Competition 2003, the self-regulation of SCPs. In these applications of WPA and the other BCI related EEG analysis mentioned earlier, the authors used various features except Entropy. Entropy is an important metric and although it has not been used in BCI related EEG analysis, it has been used along with WPA in other biomedical signal processing problems. These are pathological infant cry analysis [29], pathological voice quality assessment [30], recognition of cognitive fatigue from physiological indices [31], classification of dysphonic voices [32] and EEG based epilepsy diagnosis [33]. From these applications we see that entropy can be an important feature and must be tried along with WPA in BCI related EEG analysis as well. Four of the authors that we mentioned earlier, reported results using WPA [9,10,19,21] and applied their methods on BCI Competition datasets Ia and Ib. Since they used other features than entropy along with WPA, and were successful in these datasets, we predict that when used in combination with WPA, entropy can also be used as a feature and would perhaps perform better than those results. Therefore, in this study, we consider a novel application of WPA by combining it with log energy entropy to detect cortical negativity and cortical positivity in self-regulation of SCPs. For test purposes, we use BCI competition 2003 datasets Ia and Ib. To classify the feature vectors, we use multilayer perceptron (MLP), which is a kind of neural network efficient in classification problems. To prove its effectiveness, we compare it with k-NN and SVM classifiers.

2. Material

Our application domain is the datasets Ia and Ib of the BCI Competition 2003, as explained by Blankertz et al. [1]. These are provided by Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen.

Dataset Ia is from a healthy subject. Dataset Ib is from an artificially respirated paralyzed patient with ALS. The subjects were asked to move the cursor up and down on the screen during which their slow cortical potentials (SCP) were recorded. Subjects received visual feedback of their SCP corrected for vertical eye movements. Cortical positivity or negativity lead to a movement of the cursor up and down. Trials lasted 6 s for Ia and 8 s for Ib.

During the trials, the goal of producing cortical negativity or positivity was visually presented to the subjects by a highlighted goal at the top or the bottom of the screen. In addition, for set Ib, a vocal form of the task (up or down) was made available for the subject. The visual feedback was presented from 2 to 5.5 s for set Ia and from 2 to 6.5 s for set Ib. For the competition, only this interval of the trials was provided for training and testing in order to avoid the interference of brain responses related to goal presentation or reinforcement.

Brain activity was recorded from the scalp positions A1, A2, C3f, C3p, C4f, C4p, all referenced to Cz and the vEOG (A1/A2 = left/right mastoid, C3f means 2 cm frontal of C3, C3p 2 cm parietal of C3). Sampling rate was 256 Hz. vEOG data is not published for set Ia to avoid interference of artifacts. For set Ib subject was provided with vEOG as it provides useful information. For set Ia, 268 trials were recorded on two separate days and mixed randomly. 168 trials belong to day 1 and 100 belong to day 2. In set Ib, training and test set contain 200 trials recorded on the same day and are mixed randomly. Example signals from each data set are plotted in Figs. 1 and 2.

3. Method

Our detection and identification workflow is shown in Fig. 3. Each signal is firstly decomposed into wavelet packet subsignals. Then features are extracted from these subsignals in the form of Log energy entropy. These features are fed into a MLP for classification.

3.1. Wavelet packet decomposition (WPD)

WPD is used to decompose the signals. Wavelet packets are a generalization of wavelet bases by taking linear combinations of wavelet functions [25]. In the following explanation we take a parallel approach to Yen and Lin [7] and Wu and Liu [3]:

A wavelet function has three indices, j: index scale (integer), k: translation (integer), n: oscillation parameter; and t is time:

$$W^n_{j,k} = 2^{j/2} W^n \left(2^j t - k\right) \tag{1}$$

The first two wavelet packet functions are a scaling function and the mother wavelet function:

$$W^0_{0,0} = \varphi(t) \tag{2}$$

$$W^1_{0,0} = \psi(t) \tag{3}$$

Wavelet packet functions with higher oscillation parameters are:

$$W^{2n}_{0,0} = \sqrt{2}\sum_{\mathrm{k}} h(k) W^n_{1,k}(2t-k) \tag{4}$$