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Features Extraction Based on Subspace Methods with Application to SSVEP BCI

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ABSTRACT

The considered Human-Computer interface use Electroencephalography (EEG) activity or other electrophysiological measures of brain functions as new non-muscular channels for control and communication with smart devices and smart mobile applications for disabled persons. An approach for features extraction for Steady-State Visual Evoked Potentials-based Brain Computer Interface is presented. It employs the Multiple Signal Classification method for pseudo spectrum estimation of the EEG signal. Although not optimal and highly sensitive to the number of input parameters, the approach overcomes the insufficient frequency resolution of the most of existing frequency domain methods, thus the information transfer rate of such systems can be increased significantly. The proposed technique is tested and evaluated with an annotated database using Support Vector Machine as classification stage. The best achieved classification accuracy is above 90 %.

Keywords: Human–Computer Interface, Electrophysiological Measurements, Clustering and Classification, Brain-Computer Interface, Communication and Control

INTRODUCTION

Brain-Computer Interface (BCI) use Electroencephalography (EEG) activity or other electrophysiological measures of brain functions for disabled persons as new non-muscular channels for control and communication [1]. Developing such new communication and control technology will improve the life of disabled persons with neuromuscular disorders, as brain stem stroke, amyotrophic lateral sclerosis and spinal cord injury. BCI use depends on the interaction of two adaptive controllers: the user, who generate brain signals that encode intent and the BCI system, that translate these signals into commands that accomplish the user's intent [2]. In this sense BCI use is a skill that both user and system must acquire and maintain. The user encodes intent in signal features that the BCI system can measure. The BCI system measures these features and translates them into device commands [3]. This dependence, both initially and continually, on the adaptation of user to system and system to user is the fundamental principle of BCI. In this research we focus our activity on features extraction for Steady-State Visual Evoked Potentials-based Brain Computer Interface.

STATE OF THE ART

Brain-Computer Interface (BCI) technology provides a direct communication between human brain and the computer without using the normal output pathways of peripheral nerves and muscles. At this stage of development BCI can be successfully applicable in individuals with motor disabilities to control prostheses, speech synthesizers, assistive appliances etc. The most practical BCI solutions are those based on electroencephalogram (EEG) measurements recorded from the scalp. Most of them rely on Event-Related Potential (ERP), which is the brain response that is the direct result of a specific sensory: cognitive or motor event. There are four main types of ERP-based BCI: Steady-State Visual Evoked Potentials (SSVEP); P300; Slow Cortical Potentials (SCP) and Event-Related Desynchronization/Event-Related Synchronization (ERD/ERS). The ERD/ERS are seen as a frequency specific changes of the ongoing EEG related to a certain motor task. The changes can be an increase of power (ERS) or a decrease in power (ERD). The SCP are slow event-related, direct-current shifts in the EEG, originating from the large cell assemblies in the upper cortical layer. They

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occur from 300 miliseconds to several seconds after a certain visual stimuli. P300-based BCIs exploit a specific transient called P300 elicited in the process of decision making. Its occurrence links not to the physical attributes of a stimulus, but to a person's reaction to it. The amplitude of P300 is about several microvolts, so its detection requires statistical signal analysis of multiple trials, so the Information Transfer Rate (ITR) tends to be moderate (up to 50-70 bits/min). SSVEP are signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz the brain generates electrical activity at the same frequency (and its harmonics) of the visual stimulus [4]. In Figure 1 is shown a comparison of the mentioned techniques in terms of ITR and required time for user's training. As can be seen the SSVEP assures minimum training time at higher ITR due to its best signal-to-noise ratio and high immunity to artifacts.

The SSVEP activity is seen in all EEG channels, but it is the most prominent in the occipital part of the scalp. The frequency range form 8 to 15 Hz is preferable for SSVEP-based BCI because the highest signal-to-noise ratio is around 12 Hz, however flickering in this frequency band is annoying and tiring for the subject [5]. The frequencies ranging form 15 Hz to 25 Hz are avoided in such systems because of the increasing risk of photo epileptic seizures. Higher frequencies (25 Hz to 40 Hz) may be used as well, but the detection accuracy is lower in general.

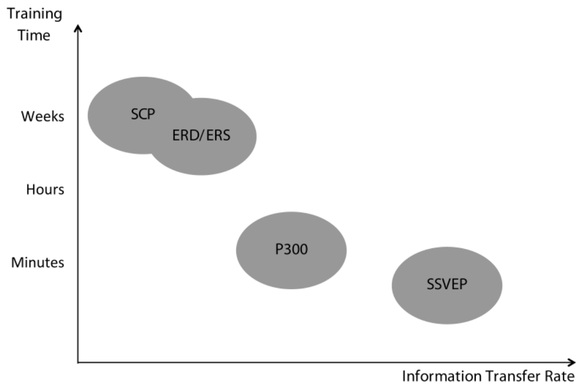

Figure1. *A comparison between SCP, ERD/ERS, P300 and SSVEP in terms of subject's training time and achieved ITR [5]*

Fourier-based algorithms for SSVEP detection are mostly used to analyze the Power Spectral Density (PSD) of an EEG epoch. They are simple and effective in terms of computation time. The frequency resolution in the key issue in FFT-based algorithms for SSVEP detection [6]. The analyzed EEG epoch has to be long enough in order to enhance the resolution, but this affects the achieved ITR. Additionally the larger window length may lead to misclassification during a change of stimuli. Some authors use continuous wavelet transforms with complex Morlet as a mother wavelet function [7]. The complex Morlet appears to be very useful solution when the SSVEP contains phase information. Although suitable for application on non-stationary signals and good combined time-frequency resolution, the estimating instantaneous frequency from a wavelet convolution is suboptimal because of frequency smoothing, and because wavelet convolution assumes frequency stationarity during the time span of the wavelet. The Hilbert-Huang Transform (HHT) is designed for analysis of non-linear and non-stationary signals. This transform includes Empirical Mode Decomposition (EMD) and Hilbert Transform (HT). EMD decomposes the EEG into narrow-band oscillations called Intrinsic Mode Functions (IMF) and for each of them the instantaneous frequency is computed. Typically the analysis is further performed considering IMFs with the maximum presence probability of the instantaneous frequencies close to the stimulus frequency [8]. A serious limitation of HHT for this purpose is the SSVEP oscillation on interest rarely falls in just one IMF. The instantaneous frequency calculation (phase integration) is also problematic and the result is inaccurate. When considering multiple EEG channels, the real-time application of HHT for SSVEP-based BCI is hard to be implemented on an average machine. The Canonical Correlation Analysis (CCA) is a multivariate statistical method to maximize the correlation between the EEG signal and the sinusoidal template signals associated to the flickering frequency in SSVEP detecting SSVEP [9]. Using pre-constructed sine and cosine reference waveforms in CCA is not a optimal method since the features of the real EEG are not considered. To address this problem a novel method called Multiset Canonical Correlation Analysis (MsetCCA) is proposed in [10]. It employs multiple linear transforms that implement joint spatial filtering to maximize the overall correlation. The authors report high accuracy, especially for small set of available channels and short window length. In [11] the ITR of SSVEP-based BCI is boosted by using a variable window length. The extracted features are based on relative powers of each harmonic of interest. The used channels are selected by criterion of minimum energy combination. The reported maximum ITR is about 130 bits/min. A serious challenge is the distinguishment of the idle-state in SSVEP BCI. An non-linear method using the approximate fractal entropy is presented in [12]. The reported sensitivity and specificity of detection are above 90 %. Recently some authors try to increase the classification robustness by combining two or more types of ERP. In [13] a hybrid between P300 and SSVEP-based BCI is investigated. The average accuracy is about 83 %.

The aim of the presented research is to investigate the accuracy of application of Multiple Signal Classification (MUSIC) method on SSVEP-based BCIs. The rest of outline of the paper is organized as follows: in the next section we give some details in features extraction and classification. In section "Experimental results" our approach is validated and evaluated using an annotated database of EEG containing SSVEP. In the last section the results are discussed and some aspects for future work are marked out.

DESCRIPTION OF THE PROPOSED APPROACH

Features Extraction using the Modified MUSIC Method

Assuming that an EEG can be represented by a series of complex exponentials with additive white noise, the MUSIC method first computes the correlation matrix $\mathbf{R}_P$ .of the time series and obtains the set of eigenverctors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_P$ and their corresponding eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_P$. The eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_M$ with large eigenvalues form the signal subspace. The remaining eigenvectors $\mathbf{v}_{M+1}, \mathbf{v}_{M+2}, \dots, \mathbf{v}_P$ form the noise subspace. The signal subspace also can be represented by group vectors of complex exponentials $\mathbf{e}(f_1), \mathbf{e}(f_2), \dots, \mathbf{e}(f_M)$, where each of them is $\mathbf{e}(f_i) = \left[1, e^{j2\pi f_i}, \dots, e^{j2\pi f_i M}\right]$. The MUSIC pseudo-PSD estimate is given by [11]:

$$PSD(f) = \frac{1}{\sum_{k=M+1}^{P} \left|\mathbf{e}^T(f)\mathbf{v}_k\right|^2}. \tag{1}$$

This PSD normally gives a good indication of the attributes of spectral components contained in a time series. However, the peaks in the PSD computed with the classical MUSIC method just indicate the frequency locations of components in a time series. These peaks occur when the denominator of the previous equation reaches zero. Therefore, the magnitude of each peak does not indicate the spectral power at the corresponding frequency. A modified MUSIC method uses the eigenvalues. $\lambda_1, \lambda_2, \dots, \lambda_P$ .as a weighting vector to compute the PSD as follows [14]:

$$PSD(f) = \frac{1}{\sum_{k=M+1}^{P} \left|\frac{1}{\lambda_k}\mathbf{e}^H(f)\mathbf{v}_k\right|^2}. \tag{2}$$

The modified MUSIC method, which also is called the Eigenvector method, can reduce the variance in the estimated PSD. When using the MUSIC method, the size of the noise subspace must be preliminary specified, which is defined as $P-M$. In general, a rough percentage can be specified of the whole space for the size of the noise subspace. With a large size of the noise subspace, a smooth PSD can be obtained but the resulting PSD may miss weak spectral peaks in the signal. With a small size of the noise subspace, a detailed PSD will be obtained that reveals weak spectral peaks. However, a too small size for the noise subspace leads to spurious peaks in the resulting PSD.

The first type of features in our approach are in fact the relative powers p_i for the peaks in PSD for frequencies $\hat{f}_1, \hat{f}_2, \dots, \hat{f}_K$ closest to those of the visual stimuli $f_1, f_2, \dots, f_K$:

$$p_i = \frac{PSD\left(\hat{f}_i\right)}{\sum_f PSD(f)}, i = 1, \dots, K. \tag{3}$$

The second type of features are measures for spectrum intensity ratio (*SI*) of the same peaks in PSD:

$$SI_i = \frac{PSD\left(\hat{f}_i\right)}{\sum_{f=\hat{f}_i-\frac{B}{2}}^{\hat{f}_i-\Delta f} PSD(f) + \sum_{f=\hat{f}_i+\Delta f}^{\hat{f}_i+\frac{B}{2}} PSD(f)}, i = 1, \ldots, K, \tag{4}$$

where B s the bandwidth (set to be 0.5 Hz in our case) and Δf is the chosen frequency resolution. The final augmented feature vector $\mathbf{o}$ is arranged as follows:

$$\mathbf{o} = \left[p_1, p_2, \ldots, p_K, SI_1, SI_2, \ldots, SI_K, \hat{f}_1, \hat{f}_2, \ldots, \hat{f}_K\right]^T. \tag{5}$$

The correlation matrix associated with the input data is calculated from all EEG channels since the SSVEP is usually presented in all parts of the scalp.

Classification

In our classification stage we use the popular Support Vector Machine (SVM) with Gaussian kernel extended to multiclass problem. The used strategy is to build a set of one-versus-one classifiers, and to choose the class that is selected by the most classifiers.

EXPERIMENTAL RESULTS

The used Dataset

For testing and evaluating of the proposed approach we have used a public available SSVEP EEG dataset [15]. It consists of 128-channel EEG data taken from four subjects in five trials. The visual stimuli are checkeboards flashing with frequencies of 8 Hz, 14 Hz and 28 Hz. The data is sampled at 256 Hz rate. In our experiments we have omitted the 28 Hz set since it is a harmonic of 14 Hz. The onset of the stimuli is at fifth second and the duration is 15 seconds. The subsets before the onsets and after the offsets are selected as training/testing data for idle-state (absence of stimulus).

Performance Evaluation Criteria

For performance evaluation, we use the standard criteria for binary classification, such as True Positive Rate (*TPR*) or Recall:

$$TPR = \frac{TP}{TP + FN}, \tag{6}$$

Positive Predictivity Value (*PPV*) or Precision:

$$PPV = \frac{TP}{TP + FP}, \tag{7}$$

and the Accuracy (*Acc*):

$$Acc = \frac{TP + TN}{P + N}, \tag{8}$$

Where *TP* denotes the number of true positives, *TN* is the number of true negatives, *FP* is the number of false positives and *FN* is the number of false negatives. The denominator in (8) denotes the total population of positives *P* and negatives *N*.

Performance Evaluation

As a preliminary experiment we selected a channel form the dataset with most prominent stimulus response in order to compare its FFT-based PSD with the pseudo-PSD evaluated with MUSIC method. As can be seen form Figure 2 the stimuli response can be distinguished with much higher reliability using the MUSIC.

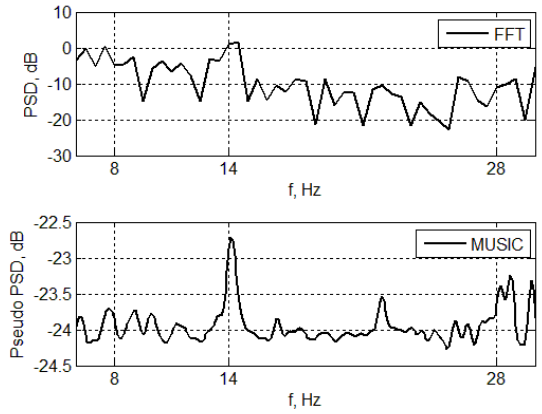

Figure2. *An example comparison between FFT-based PSD (above) and pseudo PSD evaluated using MUSIC method (below), applied on an EEG with 14Hz SSVEP stimulus. The used window size is 1024 samples and the number of components in the MUSIC method is set to 200*

We have tested and evaluated our approach considering the k-Fold method. That is, a testing part is extracted from the whole dataset. The rest of the dataset is used to train the SVM core of the classifier. This procedure repeats (10 times in our case) and the accuracy is calculated as an average of the accuracies achieved in iterations. In Figure 3 are shown the confusion matrices of SSVEP detection in two cases: without and including the absence of stimulus as a separate class. As expected the accuracy in the second case is considerably lower.

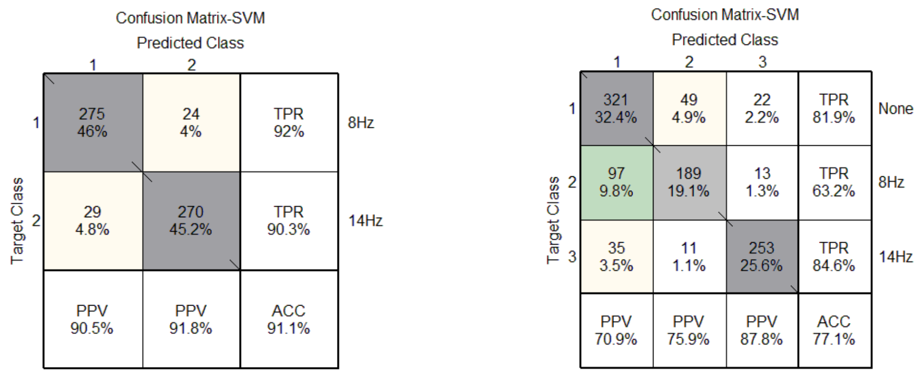

Figure3. *The confusion matrices of the performance evaluation: without detection of absence of stimuli (left) and including the absence of stimulus (right) . The percentage in each cell is referred to the total number of epochs in the testing data*

In these experiments the EEG data are divided in subsets with 256 samples overlap. Each subset is 512 samples long (corresponding to length of 2 seconds). The accuracy is also investigated for different subsets sizes (Figure 4). As can be seen when the subsets are shorter than 2 seconds, the classification is not reliable.

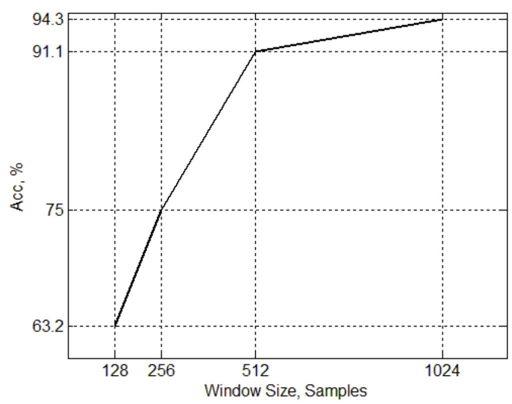

Figure4. *The classification accuracy versus different window sizes for pseudo-spectrum evaluation*

CONCLUSION

This research is devoted on features extraction for Steady-State Visual Evoked Potentials-based Brain Computer Interface. An algorithm for features extraction and classification for SSVEP-based BCI was worked out and presented. The achieved accuracy is comparable to the best available algorithms. In addition the proposed approach is capable to use shorter time epochs thus the ITR can be increased considerably. The algorithm has high sensitivity to the experimentally chosen input parameters. In future work we plan to increase the average ITR by including eye blinking as subject's confirmation of the selected object. Also, since the subspace methods for spectrum estimation produce an eigenvalue for a complex exponential the ITR can be additionally increased by detecting the phase as well.

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