A comparison of the analysis of methods for feature extraction and classification by Wavelet transform in SSVEP BCIs

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Research

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Abstract

Most of the studies in the field of Brain-Computer Interface (BCI) based on electroencephalography have a wide range of applications. Extracting Steady State Visual Evoked Potential (SSVEP) is regarded as one of the most useful tools in BCI systems. In this study, different methods which includes 1) feature extraction with different spectral methods (Shannon entropy, skewness, kurtosis, mean, variance) and wavelet transform magnitude, 2) feature selection performed by various methods (decision tree, principle component analysis (PCA), t-test, Wilcoxon, Receiver operating characteristic (ROC)), 3) classification step applying k nearest neighbor (k-NN), support vector machines (SVM), Bayesian, multiple layer perceptron (MLP) were compared from the whole stream of signal processing. Through combining such methods, the effective overview of the study indicated the accuracy of classical methods. In addition, the present study relied on a rather new feature selection described by decision tree and PCA, which is used for the BCI-SSVEP systems. Finally, the obtained accuracies were calculated based on the four recorded frequencies representing four directions including right, left, up, and down. The highest level of accuracy was obtained 91.39%.

1. Introduction

The brain-computer interface (BCI) is considered as a possible method for boosting communication and controlling the environments such as amyotrophic lateral sclerosis by which severely disabled people are able to manage their life [1].

BCI aims to create a path between the human brain and an external device such as BCI systems in order to bring human intentions into control signals. A large number of researches have recently focused on an Electro-Encephalography (EEG)-based BCI systems to accomplish the desirable communication. The signals extracted from an EEG signal such as ERP (event-related potentials), ERS (event-related synchronization), and VEP (visual-evoked potential) have been used in many perusals. They have attracted a lot of attention since VEP-based BCI systems enjoy a high information transfer rate (ITR) [2]. Among all these types, BCIs based on the Steady State Visual Evoked Potential (SSVEP) have been more emphasized. As brain responses to a visual stimulus, these significant subsets of VEP-based BCIs include high ITR, high signal-to-noise ratio (SNR), low set-time in train, and optimum steady function [3].

Firman et al. [4] applied the minimum energy combination (MEC) method to detect SSVEP from EEG signals. The method is used when the rapid and accurate recognition is necessary to attain high SNR for BCI systems. They used short segments to delete noises from EEG signals. In [5], the double stimulus frequency was used for eye stimulus in BCI systems, which leads to an increase in the performance of system. Wavelet analysis has been applied to a single EEG channel to extract its features. It was used as a conventional method to analyze EEG in order to detect sub band frequencies [6-7]. Fourier transform was applied to a single channel of EEG signals to discover the phase and amplitude of SSVEP [8, 9]. The main disadvantage of Fourier transform is that it applies the frequency of signal regardless of the time information. When both Wavelet and Fourier transform were put into application, it was possible to reach
a better signal extraction level [10-13]. In wavelet-based methods, the wavelet coefficients of sub-bands that contain stimulation frequencies are frequently selected as the feature vector and input to the classifier for SSVEP recognition [14]. In this study, we will perform a comparative analysis of methods for feature extraction, feature selection and classification in SSVEP BCIs. This study was conducted on the database built according to the experimental setup described in the future. This study is a modest contribution to the identification of the best way for SSVEP processing from the feature extraction to the classification methods. To the best of our knowledge, no study has focused on the performance of a decision tree and PCA as feature selection approaches in BCI based on SSVEP.

The remainder of this paper is organized as follows. Sections 2 discusses Experimental procedure and the four stages of signal processing; pre-processing, feature extraction approaches, features selection and the classification criteria, respectively. Section 3 presents the results, while Section 4 contains our conclusions.

2. Materials And Methods

In this study, a comparative method was adopted for classical methods in three parts of signal processing including feature extraction, feature selection, and classification. The study was conducted by using some feature extraction methods, spectral approach applying narrow band IIR filters, and wavelet transform computed at evoked frequencies. Further, six feature selection methods, and five classifiers were considered in the present study. Furthermore, the performance of each method was analyzed under a five-feature selection including decision tree, Wilcoxon, ROC, Bhattacharyya, and PCA. Fig. 1 shows the block diagram of the stream of the steps applied to the four stages of signal processing module.

2.1. Data Acquisition

The data were recorded at Brain Science Institute, Laboratory for Advanced Brain Signal Processing. Biosemi Inc. 128 active electrodes from four participants were utilized to record the related data. The participants were completely aware of the objectives of this project. In addition, they could identify the light sensitive to the epilepsy disease before recording the final data. Further, the SSVEP stimulation was recorded by reversed white and black checkered (6×6 screen). In the next procedure, the second experiment was performed with a small checkered screen at three stimulus frequencies (8, 14, 28 Hz). The sampling frequency was 256 Hz. Additionally, the participants were asked to sit at the 90 cm distance of a monitor. The SSVEP started and ended 5 seconds and 20 seconds after starting the data, respectively. We had 15 seconds of SSVEP from four batches of participants with three frequencies. Each frequency included five experiments for each participant [15, 16, 28].

2.2. Preprocessing

Wavelet is used for time-frequency analyses especially for non-stationary signals. It applies two windows to properly perform both extensive and short time-frequency analyses for low and high frequencies respectively [15]. Wavelet is a reliable way to segment the raw signal of EEG. It is useful as it enables the
researchers to analyze the signal, considering the aspects of time and frequency [16]. First, the SSVEP signals were broken into 2-second spans. Then, the discrete Wavelet transform was used for these 2-second spans. In addition, the Wavelet coefficients were decomposed. The stimulus frequencies were 8, 14, 28 Hz and accordingly Wavelet decomposition continued until every stimulus frequency was separately put in each single band. Using a two-time analysis of Wavelet decomposition level could lead us to the slight point according to the range of EEG signal, which is between 0-40 Hz. It is worth noting that the Wavelet was decomposed for four times to reach the stimulus frequencies of 8, 14, and 28 Hz at each band separately.

2.3 Feature Extraction and Selection

After decomposing signals by Wavelet, we were allowed to extract the features from the decomposed signals including Entropy Shannon, Skewness, power, Kurtosis, mean and variance. Further, the features were normalized, and the decision tree, PCA, ROC, and statistics methods were used for selecting the optimum data. The result of them, according to the higher rank, was in accordance to variables input (features) and outputs (labels). Five features were selected by using the decision tree, PCA, ROC, and statistics methods. For example, five features were selected by using the decision tree as show in Table 1. By considering the decision tree, Entropy Shannon of first channel was selected as the best feature.

Table 1. The selected features by Decision tree

| Priorities selection | Features                        |
|----------------------|---------------------------------|
| 1                    | Entropy Shannon of first channel|
| 2                    | Variance of first channel       |
| 3                    | Minimum of second channel       |
| 4                    | Power for the second channel    |
| 5                    | Maximum of the first channel    |

2.4. Classifiers

After extracting data via Wavelet and selecting the best of them, we had to use the classifiers to classify them. We applied k-NN, MLP, SVM and Bayes. MLP uses the backpropagation for its training, which is a supervised method of training. It can learn nonlinear approximation known as hidden layers [17]. SVM is a supervised machine-learning which is applied in classification of data sets. Training data divides into two groups and SVM makes a model to assign the new given data to one of two groups. It divides these two as far as possible from each other so that it could rise the resolution of groups [18-22].
3. Results

After using all of the above methods, the selected features were divided into testing and training groups. Testing and training ratios were 20% to 80%, respectively. The k-NN, MLP, SVM, and Bayes classifiers were learned on the training group, while the testing group was applied to the learned classifiers. The classifications were of a 4-class nature, among which three were related to the frequencies of 8, 14, and 48 Hz. Another frequency was related to a normal frequency.

The results of all classifiers with each featured method are reported in Table 2, along with their accuracy. In addition, $k = 7$ for k-NN and $n = 6$ (the number of neurons in hidden layer) for MLP had the best accuracy.

Table 2 shows that k-NN gained the highest accuracy among the four classifiers (91.39%) and then SVM allocated the second rate of accuracy (89.34%) with the PCA feature selection method. Further, the features selected by PCA and those given to classifiers had higher accuracy. Furthermore, the accuracy of MLP was lower for each feature selection. Finally, Bhattacharyya and Wilcoxon had weaker results compared to other feature selections methods.
3. Discussion

Comparing the results of the present study with those in other studies is difficult due to EEG (exclusively SSVEP) database, number of participants, type of Wavelet transform, decomposition level, type of classifiers, and feature extraction methods. However, the results were compared in the present study with other related ones. The information related to the database, as a pure SSVEP from EEG, was used to obtain the robust SSVEP, which was completely reliable for BCI systems and clinical applications. In addition, it allowed the researchers to reach the highest levels of accuracy and efficiency and signal-to-noise. Complexity and time-consuming calculations are considered as the most frequent problems regarding non-linear classifiers [15]. A large number of studies reported such difficulties and created overfitting problems [23]. Thus, in the present study, the linear classifications and feature extractions were implemented to obtain the highest accuracy and efficiency. The results demonstrated the highest accuracy, when linear methods are used for both classifiers and feature extractions, compared to other
recent studies. However, some cases with lower accuracy were reported in comparison with the present work. In 2006, some studies applying SVM [24] reached an accuracy of 53.98%-56.07%, and some obtained 87.5% when they improved the level of decomposition up to seven [25]. Furthermore, an accuracy of 81.48% was obtained in some studies when they decomposed Wavelet up to five levels [26] and they used k-NN. In addition, some attained an accuracy of 65.90% by using SVM. In 2011, some obtained the 85.4% accuracy by using SVM classifier [27]. It is worth noting that non-linear classifiers were difficult to be calculated due to over-fitting and time calculation in the present study [28].

4. Conclusion

The present study aimed to determine the suitable features for classifying the frequency of 8, 14, and 28 Hz, and one normal class. Further, it answered the question whether the accuracy of SSVEP extraction could be optimized by ranking the features, and using PCA and decision tree methods. The highest level of accuracy was obtained (91.39%). Furthermore, the highest accuracy was reported by using PCA method with k-NN classifier. Unlike other conducted studies, the present research was prioritized due to its classification of all processes such as signal extraction methods, feature extractions, feature selection methods and classifications, as well as its accuracy, which is shown to be the possible value. In addition, PCA, decision tree, and t-test were better than Bhattacharyya and Wilcoxon. The results of Bayes and SVM had better performance that those in k-NN and MLP. Finally, MLP had the weakest result.

Declarations

Availability of data and materials

Available.

Competing interests

The authors declare that they have no conflict of interest.

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Authors' contributions

All Authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

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Not applicable
Compliance with ethical standards

**Ethical approval** All procedures performed in studies involving human participants were in accordance with the ethical standards of the Brain Science Institute, Laboratory for Advanced Brain Signal Processing and its later amendments or comparable ethical standards.

**Informed consent** was obtained from all individual participants included in the study.

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**Figures**
Figure 1

The block diagram of BCI systems based SSVEPs