

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 7, Issue 6, June 2018

Implementation of SSVEP-Based BCI Using Spectral Features

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ABSTRACT: A brain-computer interface (BCI) is a communication system based on neural activity. Brain Computer Interfaces (BCIs) can provide severely impaired users with alternative communication paths, by means of interpretation of the user's brain activity. Among BCI operating paradigms, SSVEP is largely exploited for its potentially high throughput and reliability. Steady state visually evoked potentials (SSVEP) are signals that are natural responses to visual stimulation at specific frequencies. The signal processing algorithm is of key importance to the performance of BCI systems, and therefore plays a significant role in practical applications. The aim of this paper is to suggest and implement a robust algorithm for SSVEP-based BCI. Techniques employed for signal preprocessing, feature extraction, and feature classification are discussed. Selected methods for pre-processing are: band-pass filtering and notch filtering. These methods are compared on the basis of performance. The spectral representation of EEG signals is required as visually evoked potential affects the fundamental as well as harmonic frequencies of the particular frequency component. Thus, Fourier transform is used, along with wavelet transforms. The value comparison and classifier methods are used for feature classification.

KEYWORDS: Brain computer interface (BCI), Steady-state visual evoked potential (SSVEP).

I. INTRODUCTION

A brain-computer interface (BCI) is a direct communication pathway between an enhanced or wired brain and an external device. Brain-computer interfaces (BCIs) translate measures of brain activity into messages or commands and provide a direct connection between the human brain and a computer.

A BCI system uses direct neural activity measurements to allow people to convey their thoughts. The persons with severe disabilities are unable to communicate through any classical ways. BCIs are the most useful for such people. BCIs could be efficiently used by healthful persons as an amalgamation and complement with other interfaces, although these systems are mostly dedicated to disabled people. For these applications, BCIs must be reliable, fast and provide efficient solutions. In this regard, BCI may challenge other classical communication devices. The current BCIs are leaving the stage of laboratory demonstrators to reach the real applications. Still, many improvements are possible. Among the sections which can be improved, the signal processing part can be enhanced by using advanced classification and machine learning techniques.

In neurology and neuroscience research, steady state visually evoked potentials (SSVEP) are signals that are natural responses to visual stimulation at specific frequencies. This technique is used widely with electroencephalographic research regarding vision and attention. SSVEPs are useful in research because of the excellent signal-to-noise ratio and relative immunity to artifacts [1][5].

The signal processing algorithm is of key importance to the performance of BCI systems, and therefore plays a significant role in practical applications. The aim of this paper is to suggest and implement a robust algorithm for SSVEP-based BCI. Techniques employed for signal preprocessing, feature extraction, and feature classification are

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selected, compared and implemented, so as to build a robust algorithm.

II. RELATED WORK

A brain-computer interface (BCI) is a communication medium connecting the brain to a computer or another electronic device. Numerous techniques are being used to monitor brain function, such as electroencephalography (EEG), magneto encephalography (MEG), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) [1][2][10]. The latter three techniques are technically stringent and pricey. At present, EEG is the best choice for BCI implementation. Following are the signals which are used in commonplace, as the input of BCIs: slow cortical potentials, or rhythms recorded over sensorimotor cortex, EEG patterns associated with different mental tasks, P300 potentials, and visual evoked potentials (VEPs). BCI technology is to be further developed and utilized in an expanded way, while dealing with the issues such as the information transfer rate, the training time for users to develop competence and medical invasiveness.

Considering the above contemplation, our interests concentrate on high transfer rate, minimal training, and non-invasiveness. The input of our BCI system will be the Steady-state visual evoked potentials (SSVEPs) recorded from the occipital scalp. The system focuses on EEG activity that occurs at an individual frequency. This is the advantage. This aspect facilitates the feature extraction methods, and users require little or no training. SSVEP-based BCIs belong to dependent BCIs.

The aim of data pre-processing is to eliminate nuisance signals. Specifically, when image sizes are large and a reduced feature representation is required, the feature extraction is useful to quickly complete the tasks. In general, two techniques are used for feature classification. They can be stated as, comparison of the feature values corresponding to different stimulations and to use a classifier to generate the control command based on input signal.

III. OBJECTIVES

In general, a BCI system possesses multiple stages, including data pre-processing, feature extraction, feature classification and command translation. The figure given shows a standard flow diagram of a BCI system. It is divided into three main parts: input part (the data acquired from the subject in the EEG form), system function (data processing algorithm) and output (control of external devices).

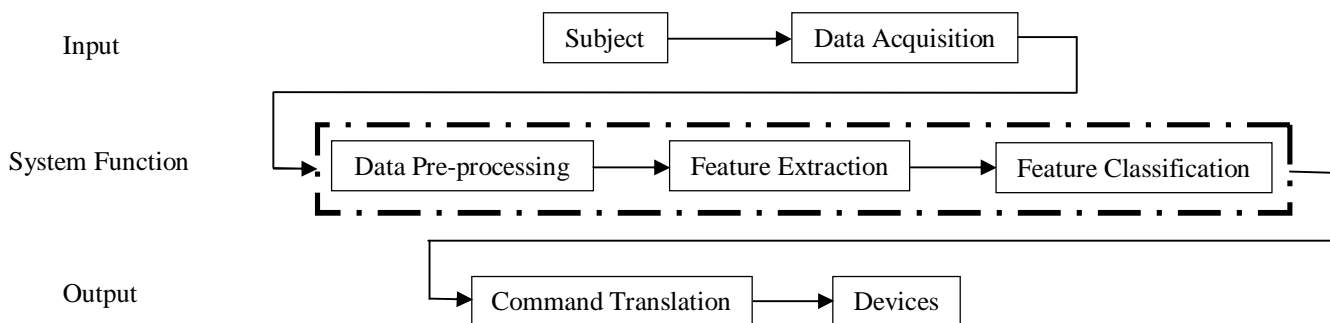


Fig.1: Simplified Overall Flow Diagram

In this paper, a comprehensive review and implementation of algorithms used for SSVEP-based BCIs is conducted. The focus is on data pre-processing, feature extraction, and feature classification. The objectives of this paper are to determine which algorithms are mostly used, what are the key issues for SSVEP signal processing algorithms, and to identify current development. This information can be used as a guideline and reference for future work.

Work Done:

- 1) Pre-processing Stage: The filtering techniques of bandpass filter and notch filter are implemented for a de-noised version of signal.

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- 2) Feature Extraction Stage: Among the three methods which are implemented, FFT is the first one. It is widely applied in SSVEP-based BCIs due to its advantages like simplicity and small computation time. The next two are wavelet-based methods, namely DWT and WPT. SSVEPs are non-stationary signals therefore FFT is not that much suitable for its processing due to frequency resolution problem. Wavelet transforms are an adjustable-window Fourier analysis, and provide good time-frequency resolution, so are suitable for processing non-stationary SSVEP signals.
- 3) Classification Stage: Here, the value comparison and classifier methods are implemented. Among them, the classifier methods include SVM and Radial Basis Function Network (RBFN).

IV. EXPERIMENTAL RESULTS

Figures show the results of the signal processing stages on the EEG signal acquired from the dataset.

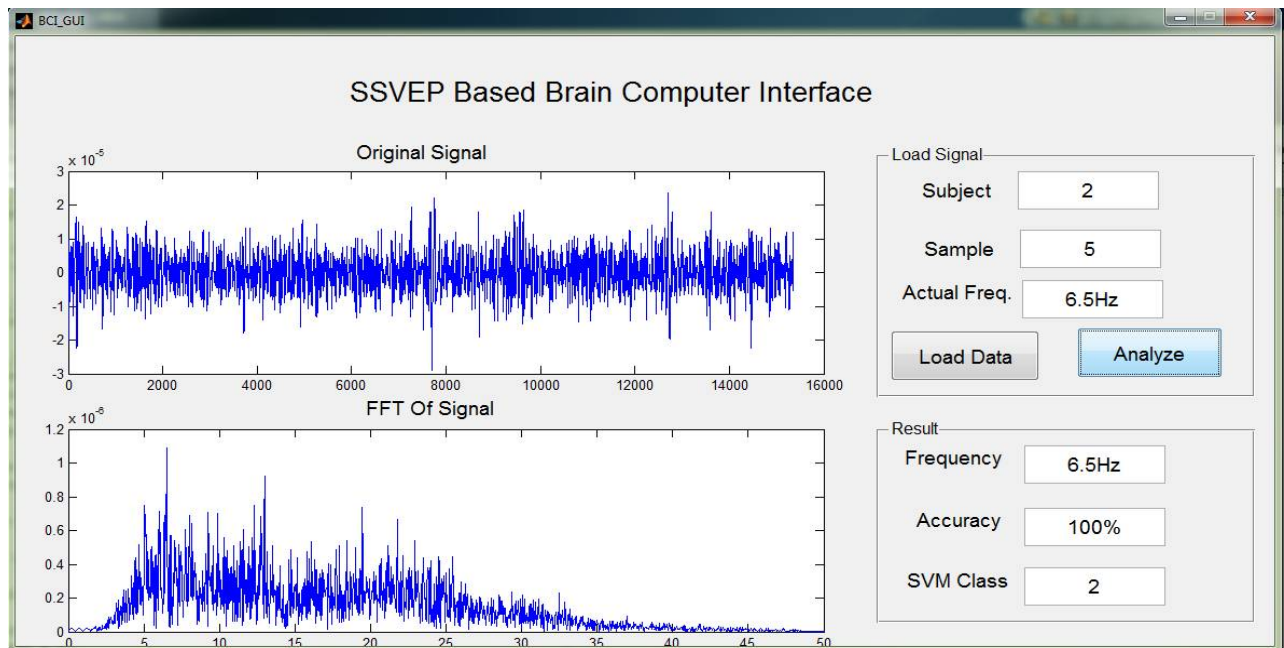


Fig. 1: The Basic GUI

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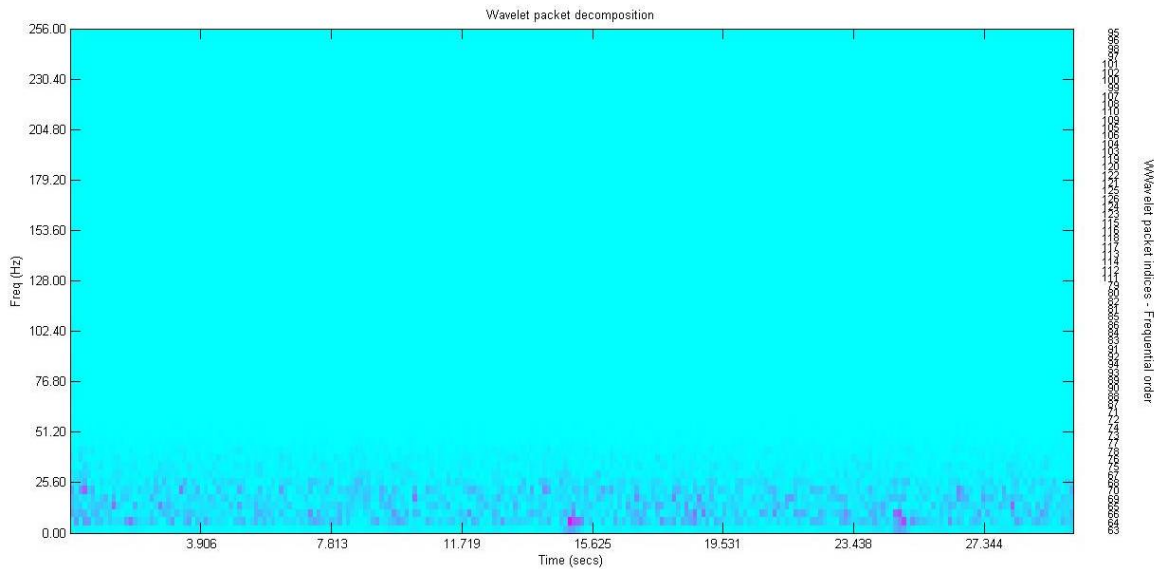


Fig.2: The Wavelet Packet Decomposition Output

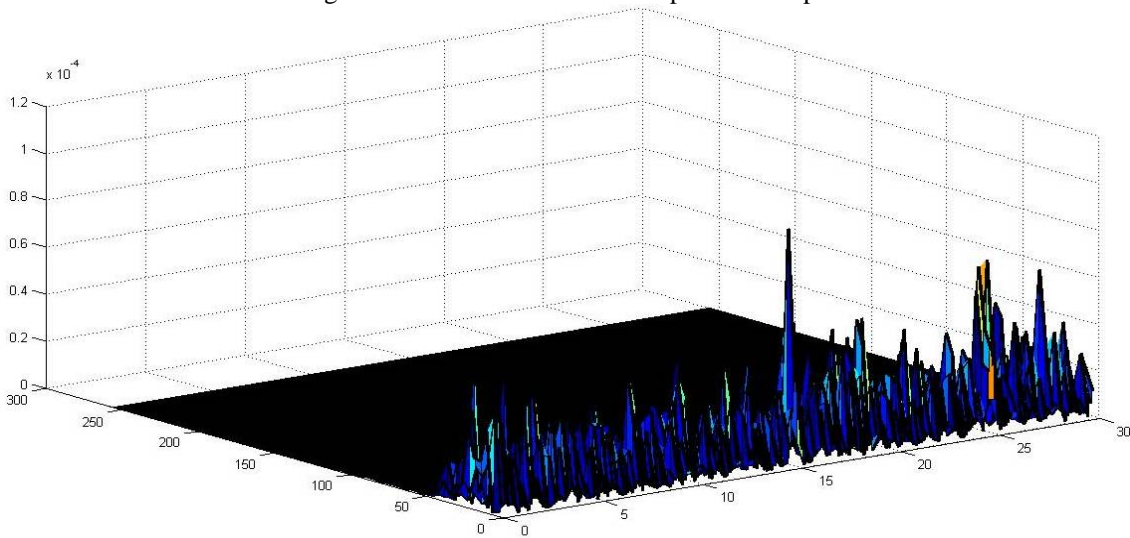


Fig.3: The Spectrum of WPT

V. CONCLUSION

This paper compares and implements the signal processing algorithms used in SSVEP-based BCIs. The results can serve as a guideline and reference for future work. The procedure of SSVEP signal processing usually includes signal pre-processing, feature extraction, and feature classification. Among the reviewed papers, band-pass and notch filters are the most commonly employed to eliminate noise.

Regarding feature extraction, the power at the stimulation frequencies and harmonics and the SSVEP phases are typical feature variables for frequency-coded and phase-coded SSVEPs.

FFT is quite popular for calculating the power corresponding to different stimulation frequencies because of its simplicity and small computation time. FFT can be used for calculating SSVEP phases. However, the Fourier transform was originally designed for linear and stationary signals. Therefore, the wavelet transform will also be

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implemented to compare with FFT. These are suitable for linear, non-stationary and nonlinear, non-stationary signals, respectively.

As for classification methods, the value comparison method and the classifier method are commonly used. Besides research on algorithms used for signal processing, it is important to use these methods efficiently in practical BCI systems, which should be easy to command by users. The goals should be lower preparation time, a user-friendly interface, and subject comfort.

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