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Research Article

Comparison Between Different Methods of Feature Extraction in BCI Systems Based on SSVEP

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Abstract

There are different feature extraction methods in brain-computer interfaces (BCI) based on Steady-State Visually Evoked Potentials (SSVEP) systems. This paper presents a comparison of five methods for stimulation frequency detection in SSVEP-based BCI systems. The techniques are based on Power Spectrum Density Analysis (PSDA), Fast Fourier Transform (FFT), Hilbert- Huang Transform (HHT), Cross Correlation and Canonical Correlation Analysis (CCA). The results demonstrate that the CCA and FFT can be successfully applied for stimulus frequency detection by considering the highest accuracy and minimum consuming time.

Keywords : BCI; CCA; Cross Correlation; FFT; Fuzzy; HHT; PSDA; SSVEP.

1 Introduction

BCI systems provide a non-muscular channel that allow the people to interact with the environment from brain activity signal measurement [1]. Several methods have been developed for measuring brain activity such as Electroencephalography (EEG), magnetoencephalography (MEG), functional resonance imaging, etc. As EEG is non-invasive technique that can be recorded by placing electrodes on the scalp, the BCI systems have been used it widely. By analyzing EEG signals we can extract features which represent users intention and varied status of human brain [2].

The different electrophysiological control signals satisfy user intention by means of monitoring brain activity, such as SSVEPs, Slow Cortical Potentials (SCPs), Sensorimotor Rhythms (mu and beta Rhythms) and P300. In 1973-1977 Vidal determined direction of eye gaze by employing SSVEP, and thus using this technique they could direct a cursor to side of user wished. VEPs are brain activity modulation that occurs after receiving a visual stimulation in the visual cortex. VEPs may be classified into Transient Visual Evoked Potentials (TVEPs) and Steady-State Visual Evoked Potentials (SSVEPs) according to frequency of visual stimulations. TVEPs occurs in reaction to visual stimuli below 6 Hz and SSVEPs in frequencies above 6 Hz. SSVEP approach provides highest information transmission rate (ITR), less training time and more safety of user.

In this paper, BCI based on SSVEP is studied.

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Over more than 30 years of studies, Birbaumer and Rockstroh demonstrated that the people can learn how control SCPs and direct object of desired direction. SCPs belong to the part of the EEG signals that shifts in EEG last a second to several seconds below 1 Hz. Negative SCPs are associated to when of movement and positive, SCPs are usually associated with reduction of activity [3]. In 1994, Wolpaw and Mefal achieved to control independent mu and beta Rhythm and used it to control cursor in two dimensions [4].

Gido Hakvoort and his colleagues studied comparison of PSD and CCA detection methods for BCI systems based on SSVEP. The results show that the CCA method performs better than the PSDA method significantly when using harmonic frequencies by attention to PSDA method has difficulties detecting harmonic frequencies, the CCA method is able to detect harmonic frequencies [5]. Xiaogang Ruan and his colleagues applied HHT to decompose signal to independent components to obtain the intrinsic mode function (IMF), then analyzing the signal from ICA based on HHT. Their experiments show that the proposed method is appropriate in feature extraction and the noise can be removed. Wang compared Minimum Energy Combination for SSVEP detection, the experiment results illustrated that CCA has higher accuracy and higher SNR than MEC [6, 7].

Currently, there exists several methods of feature extraction from signal that we survey them in the paper, such as 1) FFT method which is based on frequency analysis, although the most widely used it but it has several disadvantages such as spectral leakage and poor performance at low level signals. 2) The PSDA method which is often used as a method of SSVEP detection that is elated to signal processing in frequency domain. 3) Canonical correlation Analysis which is considered as multivariable statistical method that obtains the maximum similarity between two data sets, hence by this method can find information of interest in brain signal is hidden in highly noisy environment. 4) Hilbert- Huang transform which is time- frequency analysis due to signal that is decomposed to several time- series signals in different frequency bands. 5) Cross correlation which is statistical method that is measure of similarity of two sets of signals in signal processing. In this study we did not survey MEC and ICA, because these methods need more than one signals and in dataset we have just one signals.

In this paper presents a comparison of five methods for stimulation frequency detection in SSVEP-based BCI systems. The techniques are based on Power Spectrum Density Analysis (PSDA), Fast Fourier Transform (FFT), Hilbert-Huang Transform (HHT), Cross Correlation and Canonical Correlation Analysis (CCA). The results demonstrate that the CCA and FFT can be successfully applied for stimulus frequency detection by considering the highest accuracy and minimum consuming time.

2 METHODS

2.1 Dataset

In the experimental step, AVI SSVEP dataset of EEG signal are used. The set contains data from four healthy subjects (one woman and three man) being exposed to flickering targets in order to trigger SSVEP responses in different frequency (6, 6.5, 7, 7.5, 8.2, 9.3, 10, 12Hz). All data are recorded using three electrodes (Oz, Fpz, and Pz). The signal electrode is placed at Oz while reference is set at Fz and ground at Fpz using the standard 10-20 system for electrode placement. Reference and ground can be set to other positions such as earlobes and mastoids. The only processing applied on the data is an analog notch filter at the mains frequency (50Hz).

2.2 Cross Correlation

Cross Correlation is statistical tools applied for relationship between two random variables or two sets of data. Correlation refers to any of a broad class of statistical relationships involving dependence. The value of correlation is between 1 and 1. If we have a series of n measurements of X and Y written as X_i and Y_i where i = 1,2,..., n, then the sample correlation coefficient can be used to estimate the population Pearson correlation between X and Y. The sample correlation coefficient is written:

$$corr(X,Y) = \frac{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)^2\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2}} \tag{2.1}$$

In equation (2.1), X and Y are SSVEP responses and artificial sinusoidal signals in several frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10, 12Hz). Where $\bar{X}$ and $\bar{Y}$ are the means of X and Y respectively, which are zero, because the signals do not have DC terms.

In order to calculate cross correlation, we considered X and Y as fixed and moving signals. We move Y for 86 time and calculated maximum of cross correlations between X and Y among all 86 variable vector. Fig. 1 shows maximum cross correlation for several samples in SSVEP response of stimuli frequency 10Hz and Y in several frequencies which according to Fig. 1 most amounts in any samples belong to cross correlation between X and Y associated with flickering frequency (10Hz).

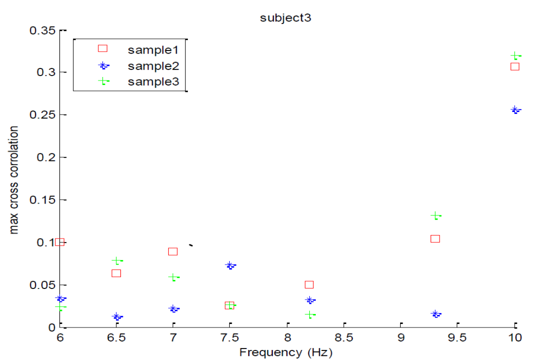

Figure 1: Max of Cross Correlation between X and Y in different frequencies for 3 samples in stimuli frequency 10Hz. for 3 samples in stimuli frequency 10Hz.

2.3 Canonical Correlation Analysis

Canonical Correlation Analysis (CCA) is introduced as a statistical multivariable technique that obtains the maximum similarity between two datasets. A variable in one set is the recorded multiple electrode signals Y and the second set is SSVEP information matrix X.

$$Y(t) = \begin{Bmatrix} y_{1(t)} \\ y_{2(t)} \\ y_{3(t)} \\ y_{4(t)} \\ y_{5(t)} \\ y_{6(t)} \end{Bmatrix} = \begin{pmatrix} sin\,(2\pi ft) \\ cos\,(2\pi ft) \\ sin\,(4\pi ft) \\ cos\,(4\pi ft) \\ sin\,(6\pi ft) \\ cos\,(6\pi ft) \end{pmatrix} \quad (2.2)$$

Consider their linear combinations as $x = X^T W_x$ and $y = Y^T W_y$ respectively, and W_y which can be found by CCA which maximizes the correlation ρ_f between x and y, by solving the following equation we have:

$$MAX\rho(X,Y) = \frac{E\left[x^T y\right]}{\sqrt{E\left[x^T x\right] E\left[y^T y\right]}} \quad (2.3)$$

The maximum of ρ with respect to W_x and , is the maximum canonical correlation. The frequency corresponding to the largest coefficient is the one of SSVEP. From Table 1, it can be observed that maximum of canonical correlation is between X and Y in the same frequency (10Hz) [7].

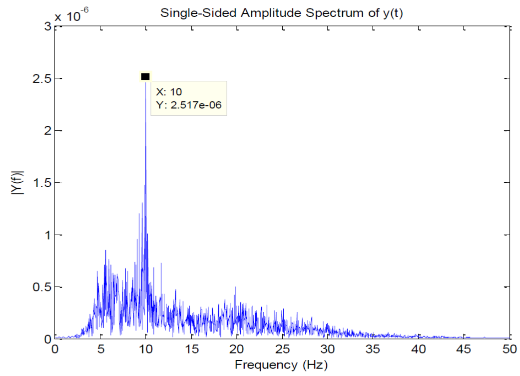

Figure 2: Frequency domain diagram of SSVEP response in stimuli frequency 10Hz.

2.4 Fast Fourier Transform

Fourier analysis converts a signal from its original domain (time) to a representation in the frequency domain. Feature extraction can be achieved in frequency domain. In most cases in BCI systems based on SSVEP is applied FFT for feature extraction, therefore in frequency spectral the largest peak is created in stimuli frequency and we can identify flicking frequency by that. In Fig. 2, the largest value related to 10Hz is shown where this frequency is flicking frequency.

2.5 Power Spectrum Density

The power spectrum density of signal is widely used in BCI based on SSVEP detection.

In this paper, the power spectrum density of EEG signal is estimated using FFT method as the feature, because the energy level is so high around stimuli frequency. The highest energy in stimuli frequency is shown in Fig. 3 [8].

Table 1: Canonical correlation between SSVEP responses in stimuli frequency 10Hz and Y in different frequencies (Hz).

Y	6	6.5	7	7.5	8.2	9.3	10
$MAX\rho(X,Y)$	0.05	0.07	0.06	0.03	0.02	0.12	0.32

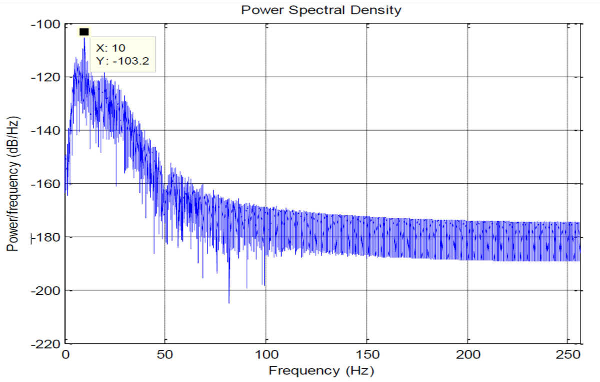

Figure 3: Power Spectrum Density of SSVEP response in stimuli frequency 10Hz.

2.6 Hilbert-Huang Transform

For first time, Norden E Huang proposed Hilbert-Huang Transform (HHT) in 1998 [6]. As we know, the natural physical processes are mostly nonlinear and no stationary. Firstly, HHT decomposes non stationary signal into a series of narrowband signal by the empirical mode decomposition (EMD), and the signal is intrinsic mode function (IMF). Secondly, the Hilbert transform is applied to the IMF. The HilbertHuang transform (HHT) is a way to decompose a signal into so-called intrinsic mode functions (IMF) along with a trend. For $\forall(t) \in R$ the EMD is given as follows: Firstly, determine $x(t)$ of all extreme points, respectively, with a cubic spline curve points to a minimum point value and a maximum point value obtained by fitting the envelope curve $e_{max}(t)$ and lower envelope curve$e_{min}(t)$. Secondly, calculate the average between (t) and $e_{min}(t)$:

$$\mu(\tau) = \left(e_{max}(\tau) + e_{min}(\tau)\right)/2 \qquad (2.4)$$

The new signal of $c(t)$ is obtained as (third step):

$$c(t) = x(t) - m(t) \qquad (2.5)$$

If $c(t)$ does not satisfy the definition of IMF, $c(t)$ is substituted with $x(t)$ repeating steps one to third; otherwise $c(t)$ is as separated IMF, and calculate the residual signal $r(t)$:

$$r(t) = x(t) - c(t) \qquad (2.6)$$

According to the results in Fig. 4, we can get 11

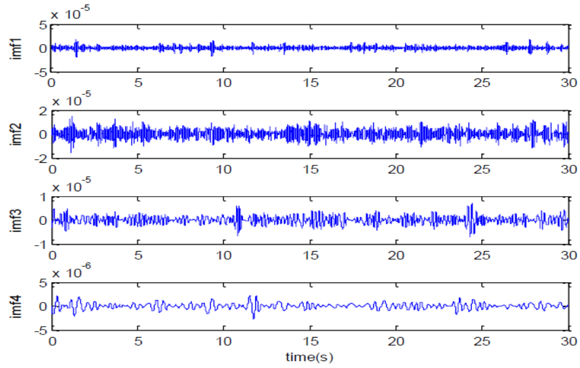

Figure 4: Signal decomposed by HHT IMF1 to IMF4.

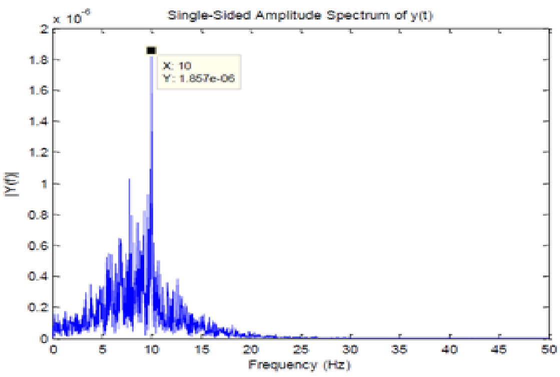

Figure 5: Frequency domain diagram of SSVEP response in stimuli frequency 10Hz by HHT.

decomposed signals from IMF1 to IMF4. In Fig. 5, we can identify flicking frequency by finding the largest peak which is created in frequency domain of IMF2 by HHT.

3 Simulation results of proposed method

In order to optimize the speed and precision of the mentioned method, FFT and CCA were cho-

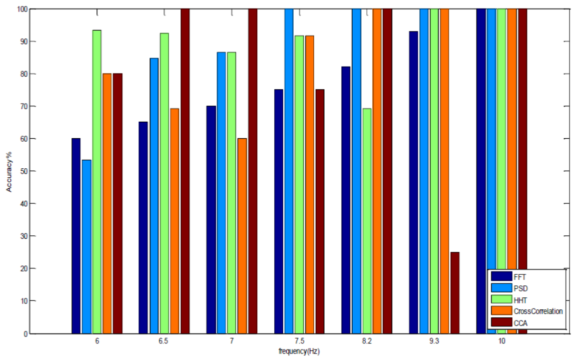

Figure 6: Accuracy for detection all of stimuli frequencies.

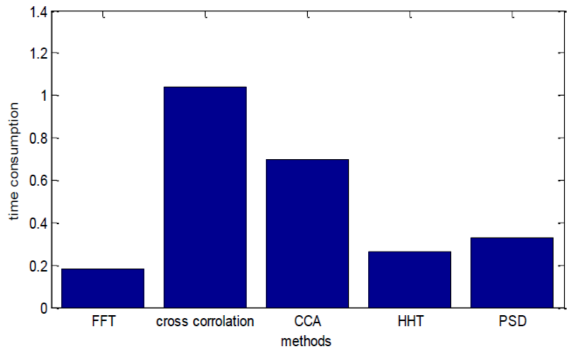

Figure 7: Time Consumption for different methods.

sen for extracting stimulus frequency in brain-computer interfaces (BCI) based on SSVEP systems. The concluded results from using these methods allowed improvement of detection in the stimulation Frequency. The simulation results in Fig. 6 illustrated that FFT method for detection stimuli frequencies consist of 6, 6.5 and 7 Hz and FFT for detection stimuli frequencies consist of 7.5 and 9.3 Hz are best.

In the above experiments, five methods were used to extract the appropriate feature, and the computation time is shown in Fig. 7. The average time of 0.19 s for FFT, 0.3 for PSD, 0.2 for HHT, 1 for Cross Correlation and 0.6 for CCA are obtained. Therefore FFT and CC methods consume the minimum and maximum time respectively.

In addition, to extract features in BCI systems based on SSVEP is applied frequency analysis such as FFT and PSD, time- frequency analysis based on Hilbert- Huang transform and statistical analysis includes Cross Correlation and CCA in order to compare them. According to Fig. 8, for first user, FFT and PSD have most, for second user CCA method has highest accuracy and HHT method is least, for third user CCA and Cross Correlation have most accuracy and HHT has least accuracy and fourth user FFT and PSD have highest accuracy and HHT, FFT and PSD has least accuracy.

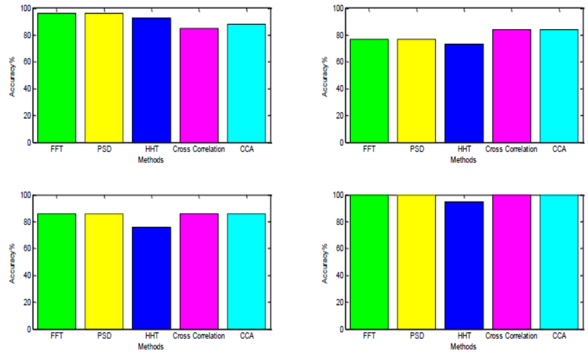

Figure 8: Accuracy of all of methods users (top left- user1, top right- user 2, down left- user 2 and down right- user4).

4 Conclusion

In this study five methods for stimulation frequency detection in BCI systems based on SSVEP have been presented. The techniques were based on the methods of PSDA, FFT, HHT, CC and CCA. The results demonstrate that the CCA and FFT can be successfully applied for stimulus frequency detection by considering the highest accuracy and minimum consuming time.

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