Novel Detection Features for SSVEP Based BCI: Coefficient of Variation and Variation Speed

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Abstract

This paper introduces novel detection features for the steady-state visually evoked potential (SSVEP) based brain computer interfaces. The coefficient of variation and variation speed features were developed using the stability of SSVEP response. The developed features were tested on 13 subjects. On this dataset, for which the chance level is 12.5%, about 70% detection accuracy was obtained. Based on these results, it is considered that the coefficient of variation and the variation speed can be used as discriminative features for SSVEP. By using familiar SSVEP features and developed features together, higher SSVEP detection accuracy can be obtained. By this procedure the performance of single channel SSVEP based BCI systems can be improved.

Keywords: Brain computer interface; Steady-state visual evoked potential; detection feature; stability

1. Introduction

Severely disabled people can regain some functions by means of a new augmentative technology known under the name of Brain–computer interface (BCI). This technology can be used also to enhance functions in healthy individuals. A BCI system measures brain activity. It generates an artificial output that does not depend on the peripheral nerves and muscles. Thus, this artificial output can be used to further ensure coordination between the brain and its environment (Wolpaw and Winter Wolpaw 2012).

The SSVEP response is a continuous and periodic signal and it is induced through repeated visual stimulus ranging from 3.5 Hz to 75 Hz. The signal, together with its harmonics, has near sinusoidal waveforms. The frequency of the SSVEP signal is the same as the frequency visual stimulus. The signal has almost constant amplitude and phase. Using SSVEP response in BCI brings some advantages: high information transfer rate, non-invasiveness and does not need intensive user training (Vialatte et al. 2010).

For target stimulus detection, in most of SSVEP based BCI, two detection features are commonly used: Spectral content (Bin et al. 2009; Diez et al. 2013; Fan et al. 2015; Cao et al. 2015; Abu-Alqumsan and Peer 2016) and phase information (Molina et al. 2010; Lopez-Gordo et al. 2010; Manyakov et al. 2012; Yeh et al. 2013; Tong and Zhu 2015). Using canonical correlation analysis (CCA) based detection methods, high detection accuracy is achieved even in short-term electroencephalographic (EEG) signals (Nakanishi et al. 2015). However, these methods use multiple channels. User friendliness of BCI systems is also important as performance for real-life applications. Increased number of channels reduces the user friendliness. Hence single channel SSVEP based BCI is more suitable for real-life applications. However available single channel SSVEP detection methods cannot provide the enough accuracy. Different features that define the signal may be the solution to increase the detection accuracy. Stability of SSVEP signal is a characteristic feature that distinguishes SSVEP response from spontaneous EEG signal. This feature can be used to detect the SSVEP signal.

SSVEP oscillates at the fundamental frequency and harmonics of the visual stimulus. Signals belonging to other brain activities also contain components with the same frequency, and the intensity of these background signals varies with time. When the EEG signals are recorded at the scalp, due to the interference of the background signal, the component corresponding to the stimulus frequency of the EEG signal is unstable. Nevertheless, it can be predicted that the change in intensity of spontaneous EEG will be sharper than change in intensity of the EEG component with SSVEP. Based on this situation, stability can be beneficial in detecting the SSVEP signal.

Furthermore, since the intensity of spontaneous EEG signals is larger than the intensity of evoked potentials, the examination of the stability of the SSVEP signal becomes important.

In this study, new detection features called as coefficient of variation and variation speed are investigated by taking advantage of the stability of the SSVEP signal. The proposed features are tested on SSVEP datasets. Detection accuracy of about 70% is obtained with 2-second EEG signals from 13 subjects. The obtained results show that the proposed parameters are discriminative features for SSVEP. Proposed features can be used together with spectral content and phase information to increase the detection accuracy. Thus, the performance of single channel SSVEP based BCI can be improved.

2. Method

The flickering visual stimulus induces a SSVEP response. The SSVEP response is periodic and stable over time. Based on this, the stability of the SSVEP response can be used as detection feature for SSVEP based BCI.

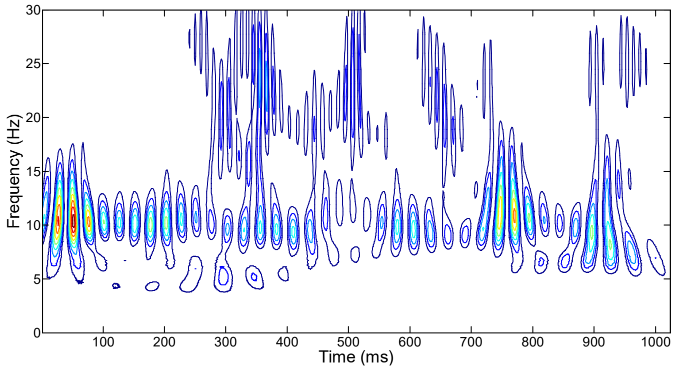

Figure 1: Time vs frequency analysis of 10 Hz SSVEP response

The stability of the SSVEP signal was examined by using wavelet analysis (Wu and Yao 2008). Since there is a trade-off between time and frequency resolution in wavelet analysis, examining the stability of SSVEP with wavelet analysis is getting harder in systems where the visual stimulus frequencies are close to each other, as shown in Figure 1.

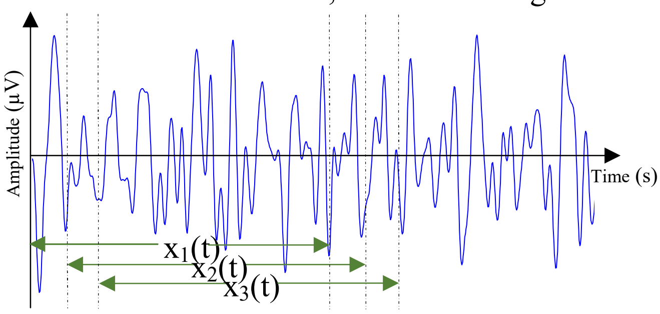

Figure 2: Overlapped EEG segments

In this study, the short time Fourier transformation (STFT) is used to examine the stability of the SSVEP. As the frequency resolution decreases with window size, overlapped EEG segments

(Figure 2) that give sufficient frequency resolution are used. Coefficient of variation and variation speed detection features are proposed by using frequency spectrum of the segments.

In Equation 1, *x(t)* sequence defines overlapped EEG segments in time domain, and in Equation 2 the *x(f)* sequence defines these segments in frequency domain and *m* is number of segments.

$$x(t) = [x_1(t)\ x_2(t)\ x_n(t) \ldots x_m(t)] \tag{1}$$

$$x(f) = [x_1(t)\ x_2(t)\ x_n(t) \ldots x_m(t)] \tag{2}$$

For examining the stability of the SSVEP response, the differences between the amplitude of the stimulus frequency and the amplitude of the neighboring frequencies in consecutive EEG segments are used. With the use of the amplitude differences, the effects of intensity variation caused by the spontaneous EEG in the examined frequency region are reduced. In Equation 3, $\Delta(f_i)$ defines this amplitude differences and f_i defines stimulus frequency. $\Delta_n(f_i)$ is calculated as shown in Equation 4.

$$\Delta(f_i) = [\Delta_1(f_i)\ \Delta_2(f_i)\ \Delta_n(f_i) \ldots \Delta_m(f_i)] \tag{3}$$

$$\Delta_n(f_i) = \left|x_n(f_i)\right| - \frac{1}{L}\sum_{k=1}^{L}\left|x_n(f_{nb_k})\right| \tag{4}$$

In Equation 4, f_{nb_k} defines neighboring frequency and L defines number of neighboring. Δ sequences are shown graphically in Figure 3.

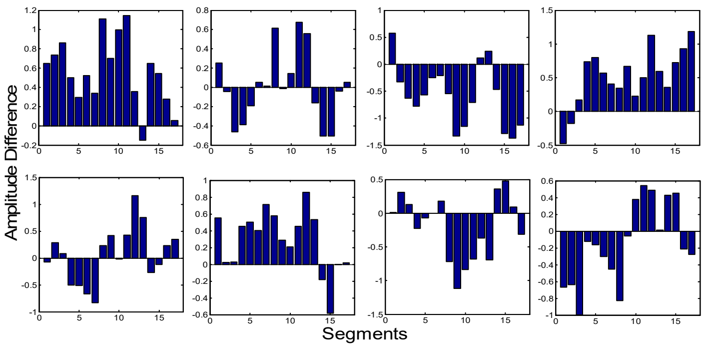

Figure 3: $\Delta(f_i)$ sequences at different frequencies

The first developed parameter for the stability of SSVEP is the coefficient of variation (CV). The variation in $\Delta(f_i)$ sequence that is obtained at EEG component with SSVEP response is expected to be less than the other sequences. Equation 5 shows the calculation of CV. $\sigma_{\Delta(f_i)}$ is the standard deviation of $\Delta(f_i)$ sequence. $\mu_{\Delta(f_i)}$ is the averaged value of $\Delta(f_i)$ sequence.

$$CV_{\Delta(f_i)} = \frac{\sigma_{\Delta(f_i)}}{\mu_{\Delta(f_i)}} \tag{5}$$

$$\mu_{\Delta(f_i)} = \frac{1}{m}\sum_{n=1}^{m}\Delta_n(f_i) \tag{6}$$

$$\sigma_{\Delta(f_i)} = \sqrt{\frac{1}{m}\sum_{n=1}^{m}\left(\Delta_n(f_i) - \mu_{\Delta(f_i)}\right)^2} \tag{7}$$

The second developed parameter for the stability of SSVEP is the variation speed (VS). It is expected that the amplitude differences for the component with the SSVEP response in consecutive EEG segments will change more smoothly. For calculating VS, the difference of sequential values in $\Delta\ (f_i)$ was used. The total difference throughout the $\Delta\ (f_i)$ sequence is shown in Equation 8 as $D_{\Delta(f_i)}$. VS is calculated as shown in Equation 9. The total difference is divided by the average value of $\Delta\ (f_i)$ for comparing sequences with different average amplitude.

$$D_{\Delta(f_i)} = \frac{1}{m-1}\sum_{n=1}^{m-1}\left|\Delta_{n+1}(f_i) - \Delta_n(f_i)\right| \tag{8}$$

$$VS_{\Delta(f_i)} = \frac{D_{\Delta(f_i)}}{\mu_{\Delta(f_i)}} \tag{9}$$

3. Experimental procedure

In order to test the developed features, the SSVEP datasets recorded in (Nakanishi et al. 2014) is used. Flickering boxes had been presented on 24-inch LCD monitor with a refresh rate of 75Hz. 32 visual stimuli had been generated with 8 different frequencies (8 Hz, 9 Hz, …, 15 Hz) and 4 different phases (0^o, 90^o, 180^o, 270^o) as shown in Figure 4. Thirteen healthy adults had participated in the experiments. EEG data had been recorded by 16 electrodes (FPz, F3, F4, Fz, Cz, P1, P2, Pz, PO3, PO4, PO7, PO8, POz, O1, O2 and Oz). The sampling rate had been 512 Hz.

The datasets are grouped into 4 groups. The 0-degree stimuli formed the 1st group, the 90-degree stimuli the 2nd group, the 180-degree stimuli the 3rd group and the 270-degree stimuli the 4th group. Thus, it is made possible to test the developed features in more datasets.

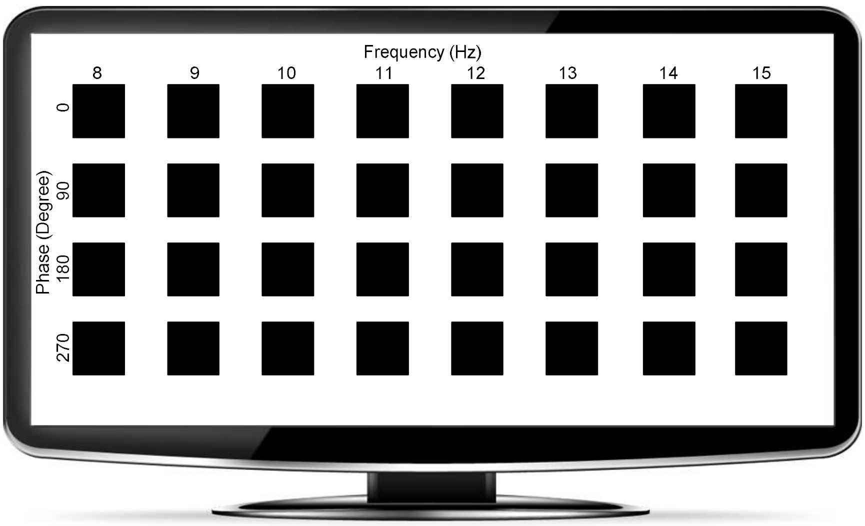

Figure 4: Visual stimuli

4. Data analysis

The EEG data are band-pass filtered from 7 Hz to 30 Hz using an infinite impulse response (IIR) filter. The EEG signal recorded from Oz channel is used for SSVEP detection. SSVEP detection is carried out by power spectral density (PSD), CV and VS on 2 second EEG data. The window length for CV and VS is taken as 1 second. The windows are shifted to 32 samples to create overlapped EEG segments. Neighboring frequencies are considered *f-0.5 Hz* and *f+0.5 Hz* where f is the stimulus frequency. The power of the first and the second harmonics of the stimulation frequencies are utilized for PSD analysis.

Value comparison method is used for feature classification. The target visual stimulus frequency f satisfies the Equation 10, 11 and 12. In (10, 11 and 12), K represents the number of stimuli.

$$f=argmax_i\, PSD(f_i),\ s.t.\ i=1, 2, \ldots, K \quad (10)$$
$$f=argmin_i\, CV(f_i),\ s.t.\ CV(f_i)>0, i=1, 2, \ldots, K \quad (11)$$
$$f=argmin_i\, VS(f_i),\ s.t.\ VS(f_i)>0, i=1, 2, \ldots, K \quad (12)$$

5. Results

When the results in Figure 5 are analyzed, it is seen that CV and VS features provide detection results similar to PSD, which is a familiar feature. Considering that the chance level is 12.5% in these dataset, CV and VS can be used as discriminative features for SSVEP. Also on some subjects, like S3 on 1st and 4th datasets, and S11 on 1st, 2nd and 4th datasets, the proposed features have given clearly better detection results than PSD.

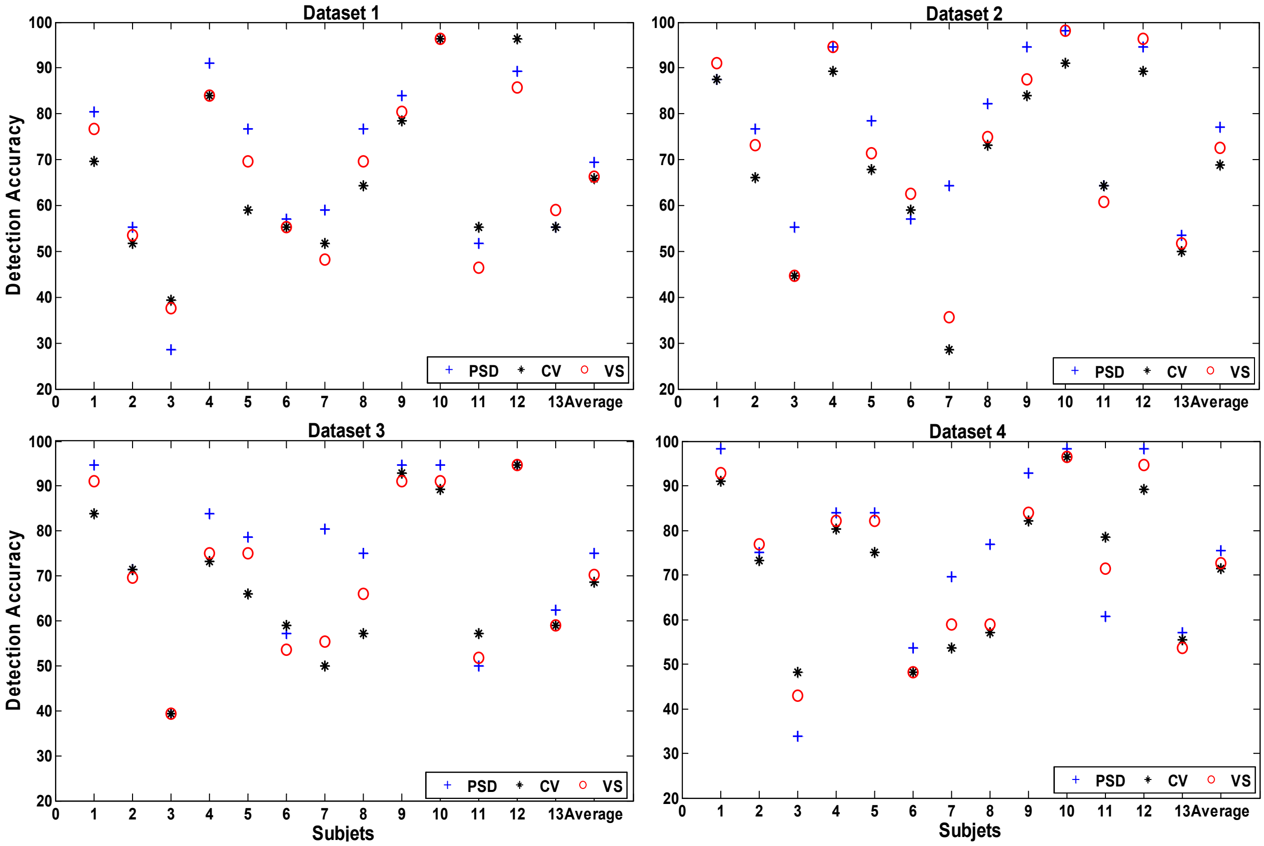

Figure 5. SSVEP detection accuracies by using PSD, CV and VS features

6. Discussions and Conclusion

Spectral content and phase information of EEG is used to detect target stimulus in SSVEP based BCI systems. CV and VS features can also be used to detect SSVEP as shown in results section.

Despite better detection accuracies are obtained by PSD in most of the EEG data, the proposed features have results in better detection accuracies in some EEG data. This suggests that, using familiar features and suggested features together, a method that gives higher SSVEP detection accuracy can be developed. Also, considering the phase stability, the coefficient of variation and variation speed features can be improved. Thus, the characterization of the SSVEP signal can be better represented.

For real life BCI applications, cost and user friendliness are important besides information transfer rate (ITR). This makes single channel BCI performance more important. By using familiar SSVEP features and proposed features together, single channel SSVEP based BCI providing high ITR can be developed.

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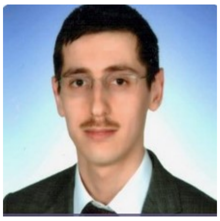

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