CYCLOSTATIONARY-BASED DETECTION OF STEADY-STATE VISUALLY EVOKED POTENTIAL SIGNALS RECORDED FROM EEG

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ABSTRACT

Steady-state visual evoked potentials (SSVEP) are a class of signals obtained from the electroencephalogram (EEG) that are used in conjunction with brain-computer interfaces (BCIs). Inducing SSVEP signals requires flickering lights as stimuli, typically in the range of 5-45 Hz. However, due to low signal-to-noise ratio (SNR), SSVEP signals generated in certain frequency ranges can be difficult to detect. This paper studies cyclostationary-based detection for SSVEPs, which is a popular method for signal detection in low SNR environments, but whose application in the context of BCI systems has received only limited attention in the BCI research community. The results presented in the paper demonstrate that cyclostationary-based detection of SSVEP using spectral correlation density (SCD) performs as well as canonical correlation analysis (CCA), which is the most widely used method of SSVEP classification.

***Index Terms*—** Brain computer interface, steady state visually evoked potential, detection, cyclostationarity, canonical correlation.

1. INTRODUCTION

A BCI uses signals from the brain to control an external device, such as moving a prosthetic limb or moving a computer cursor on the screen. BCI systems date back to the 1970s when the ability to communicate in Morse code using EEG activity associated with eye movement was demonstrated [1]. Since then, research in the area of BCI systems evolved in two main directions. The first has focused on the development of assistive communication devices for patients with severe neuromuscular disorders (such as Amyotrophic Lateral Sclerosis, for example) and are suffering from "locked in syndrome". More recently, other uses for BCI technology are being researched including rehabilitation and consumer applications such as neurogaming or virtual training environments. We note that SSVEP-based BCI systems are suitable for applications where users are able to control their gaze and respond to visual stimuli.

There are multiple methods of obtaining brain activity for driving a BCI system, with the most common being from the EEG. Active BCIs, such as those that use sensory motor rhythms (SMRs), are controlled by spontaneous brain activity. In contrast, passive BCIs, such as those that use the P300 evoked potential or SSVEP, rely on sensory stimuli to evoke the brain activity. SSVEP is produced by the brain in response to oscillating or flickering visual stimuli. SSVEP shows promise in the BCI context as they offer a relatively high data rate and require no training for classification [2].

An important consideration when working with EEG signals is noise removal to enhance their SNR. Typically, this is accomplished by averaging signals recorded from multiple trials, and is most effective when noise is white and zero mean, leading to improvements in SNR that increase with the number of trials averaged. However, the time required to obtain a sufficient number of trials for an acceptable SNR can be prohibitive for some real-time BCI systems.

As an alternative to noise removal, methods for detecting EEG signals with low SNR may also be pursued. This approach is commonly used in modern wireless communication systems to detect active signals in low SNR environments, and uses cyclostationary properties of digitally modulated signals for signal detection in spectrum sensing applications [3], for modulation classification [4], or for estimating signal parameters [5]. Recently, the use of a cyclostationary-based approach was reported for detection of concatenated P300 evoked potentials [6]. This motivates the work presented in this paper, which studies cyclostationary-based detection of SSVEP.

The paper is organized as follows. Section 2 provides an overview of SSVEP and of the signal processing techniques used for detection and classification, followed by derivation of the spectral correlation density (SCD) used in the cyclostationary-based detection of SSVEP in Section 3. Data collection and analysis of numerical results are presented in Section 4. Section 5 concludes the paper with final remarks.

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2. STEADY-STATE VISUALLY EVOKED POTENTIALS

SSVEP is a response to visual stimulation from 3.5 to 100 Hz and can be observed in the EEG signal over the visual cortex [7]. BCI systems using SSVEP generally include displays with multiple target regions or icons, each with a distinct flickering frequency. When the user focuses on a particular target region or icon, an SSVEP is generated at harmonics of the associated target flickering frequency. SSVEP is observed at the first harmonic of the stimulus frequency f_s and often in the second and third harmonics [8].

The BCI system examines the power spectra from EEG channels over the visual cortex to detect the signal and classify the desired target. SSVEP signals are significantly larger in lower frequency ranges with the largest signal appearing around 15 Hz [9]. The meninges, skull, and scalp layers act as a low pass filter [10] which is a major contributor to the $1/f$ characteristic of EEG and the weaker SSVEP signals at higher frequencies. There are issues however with low frequency (< 20 Hz) SSVEP-based BCIs. Low frequencies have been reported to be visually irritating to the user, cause eye fatigue, and are more likely to cause an epileptic seizure [11]. Therefore, an SSVEP-based BCI system above the flicker fusion threshold has particular advantages. The flicker fusion threshold is the lowest frequency at which a flicking light is perceived to be steady state, and for the purpose of an SSVEP BCI this is approximately 40 Hz. High frequency SSVEP-based BCI systems have been considered, but because the SSVEP signal is weaker at these frequencies these systems have lower data rates, higher BCI illiteracy rates, and reduced accuracy as compared to their low frequency counterparts [12]. Unique modulation methods have been proposed which utilize a higher carrier frequency in combination with a lower modulating frequency, but the lower frequency can still be observed by the user [13]. Thus, in order for a high frequency SSVEP-based BCI system to be successful, alternative detection methods must be explored.

Multiple methods for extracting and classifying SSVEP signals from EEG have been considered. Generally non-parametric methods such as the periodogram are used due to their superior performance to parametric methods in the presence of noise [14]. Further, canonical correlation analysis (CCA) is often used to detect SSVEPs and has been demonstrated to outperform techniques based on power spectral density (PSD) analysis [15]. CCA relies on the SSVEP signal being composed of a linear combination of the BCI stimulus frequency harmonics. Using CCA, canonical variables, or linear combinations of spatial harmonic frequencies, for two signal arrays are found so that the correlation between the two is maximized. In this case one signal array contains EEG signals from channels of interest while the other contains a set of template sinusoids at the stimulus harmonics. CCA is performed multiple times, once for each BCI flickering frequency; the largest correlation value is the hypothesized target [16]. One of the major benefits of using template signals is that training data is not required for classification. Cyclostationary-based detection of SSVEP is similar to CCA in that it also takes advantage of the SSVEP signal harmonics and can be implemented without training data.

3. CYCLOSTATIONARY-BASED DETECTION OF SSVEP

Cyclostationary-based detectors, also referred to as feature detectors, exploit specific cyclic statistical properties of non-stationary signals to identify specific features of the signals such as, for example, carrier frequencies, symbol period [5], or other periodic features [4] for digitally modulated communication signals. In addition, cyclostationary feature detectors benefit from the stationary properties of additive noise, which enables them to distinguish signals from noise at low SNRs [17].

A non-stationary signal is said to be second-order cyclostationary if its time-varying mean and autocorrelation functions are both periodic with period T, that is

$$\mu_x(t) = E\{x(t)\} = E\{x(t+T)\}, \tag{1}$$

$$\begin{aligned} R_x(t,\tau) &= E\{x(t)x^*(t+\tau)\} \\ &= E\{x(t+T)x^*(t+T+\tau)\}. \end{aligned} \tag{2}$$

Because $R_x(t,\tau)$ is cyclic it can be expanded using a Fourier series expression [17]

$$R_x(t,\tau) = \sum_{\alpha \in A} R_x^\alpha(\tau) e^{-j2\pi\alpha t}. \tag{3}$$

Here, α is the cyclic frequency, A is the countable set of cyclic frequencies, and $R_x^\alpha(\tau)$ is the cyclic autocorrelation (CAC) function with respect to α. Using the definition of the inverse Fourier transform the CAC can be expressed as

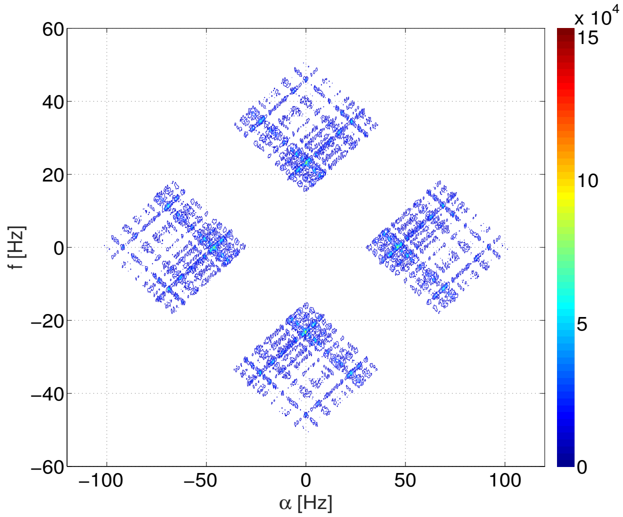
$$R_x^\alpha(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} R_x(\tau) e^{-j2\pi\alpha t} dt \tag{4}$$

We note that for cyclostationary signals $R_x^\alpha(\tau)$ is finite for $\alpha = n/T$ and 0 otherwise. However, for stationary signals $R_x^\alpha(\tau)$ is 0 except at $\alpha = 0$. If we assume that the EEG signal is comprised of a linear combination of the periodic SSVEP signal and non-periodic noise then the CAC is independent of the amplitude of the additive noise assuming the noise is not periodic.

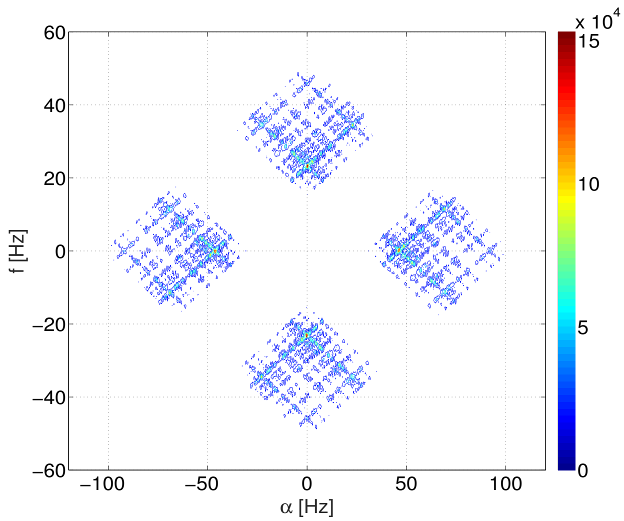
$$\begin{aligned} x(t) &= s(t) + n(t) \\ R_x^\alpha(\tau) &= R_s^\alpha(\tau) + R_n^\alpha(\tau) \\ R_x^\alpha(\tau) &= R_s^\alpha(\tau), \text{ for } \alpha \neq 0 \end{aligned} \tag{5}$$

Using the CAC, the SCD can be determined as the Fourier transform of the CAC

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau. \tag{6}$$



(a) No noise added.



(b) 30 dB noise added.

Fig. 1. SCD for a 23 Hz SSVEP signal obtained from EEG channel O2 and filtered using a 15-52 Hz bandpass filter.

The spectral correlation density is known by multiple other names including cyclic spectral density and spectral correlation function. An alternate way of considering the SCD is the normalized correlation between two spectral components of $x(t)$ at frequencies $(f+\alpha/2)$ and $(f-\alpha/2)$ over the observation interval Δt. Thus, the SCD can also be expressed as

$$S_x^\alpha(f)=\lim_{\Delta t\to\infty}\lim_{T\to\infty}\frac{1}{T}\int_{-\Delta t}^{\Delta t}X\Big(t,f+\frac{\alpha}{2}\Big)X^*\Big(t,f-\frac{\alpha}{2}\Big)dt. \quad (7)$$

Considering an SSVEP produced by a visual stimulus with frequency f_s, we note that its SCD will have primary peaks due to the first harmonic at the $(\pm f_s, 0)$ and $(0, \pm 2f_s)$ pairs, and secondary peaks due solely to the second harmonic will be found at$(\pm 2f_s, 0)$ and $(0, \pm 4f_s)$. Further, peaks at $(\pm 1.5f_s, \pm f_s)$, and $(\pm 0.5f_s, \pm 3f_s)$ result due to the correlation of the first and second harmonics. Figure 1 illustrates this aspect with examples of an SCD of a 23 Hz SSVEP signal which has been filtered using a 15-52 Hz bandpass filter.

We note that, cyclostationary-based detection has a high computational requirement due to the large number of complex multiplications required, and that this problem is compounded when the cyclic frequency is unknown. However, the classification methodology used in our analysis required computation for a finite set of frequencies and cyclic frequency, thus minimizing computations.

4. DATA COLLECTION AND NUMERICAL RESULTS

To study the performance of cyclostationary-based detection of SSVEP, data was obtained from a single healthy male subject with corrected-to-normal vision. This subject was known to have a strong SSVEP response which could be detected with high accuracy using the CCA classification technique described in [16], and the classification accuracies of the two methods have been compared.

4.1. Data Collection Methodology

The subject was placed in a dark room approximately 60 cm in front of an array of 8×8 green LEDs which were placed at eye level. The LEDs flickered as to produce a 50% duty cycle square wave. The use of the square wave over a triangle or sine wave as well as the duty cycle of the square wave was selected in order to yield the strongest SSVEP response [18].

Five trials were conducted each with a different stimulus frequency: 17 Hz, 19 Hz, 21 Hz, 23 Hz, and 25 Hz. The duration of each trial was 20 seconds. A 32-channel EEG was collected using the standard active-wet electrodes 10/20 electrode placement. Signals were amplified using a gtec g.USBamp and sampled at 256 Hz, and O2 was utilized for the analysis.

The data from the 20 second trials was segmented into ten 2-second blocks. These data blocks were filtered using a zero-phase 15-52 Hz bandpass FIR filter. The filter passband was intentionally set such that it was 2 Hz below the lowest frequency and 2 Hz above twice the highest frequency. The SCD of the filtered 2 second data blocks was found using a frequency resolution of 0.5 Hz and a cyclic frequency resolution of 0.25 Hz.

Similar to CCA, a rudimentary classification method was employed that did not require training. For each $f_s \in \{17, 19, 21, 23, 25\}$ the SCD for the 2 second block was evaluated at the points (f, α) equal to: $(f_s, 0)$, $(0, 2f_s)$, $(2f_s, 0)$, $(0, 4f_s)$, $(1.5f_s, f_s)$, and $(0.5f_s, 3f_s)$. The value of f_s corresponding to the maximum of the 25 points evaluated was the assumed frequency. Additional classification techniques were evaluated, including 2-D correlation with template SCAs (similar to the template signals used in CCA). However, classification using the maximum point method described obtained optimal results.

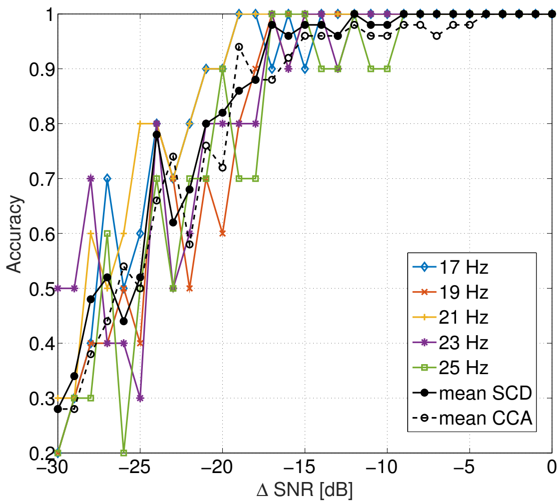


Fig. 2. Comparison of classification accuracies for CCA and cyclostationary-based detection for a single noise trial.

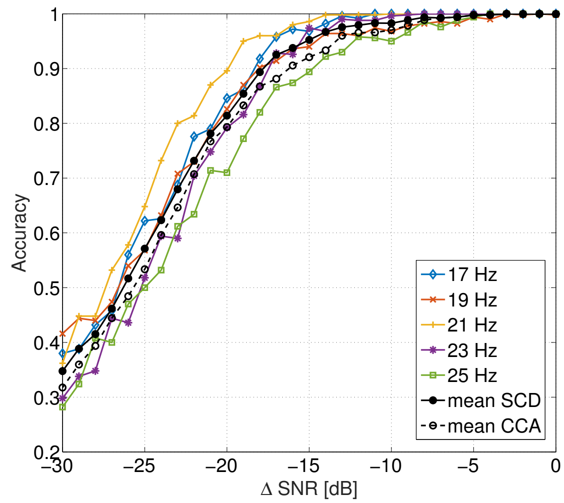


Fig. 3. Comparison of classification accuracies for CCA and cyclostationary-based detection averaged over 50 noise trials.

In addition to determining classification accuracy using the signal collected, this analysis evaluated the impact of increasing noise corrupting the desired signal. This was done to determine the tolerance of cyclostationary-based detection to additive noise as it is often used in low SNR environments. Prior to segmenting or filtering the signal, additive white Gaussian noise (AWGN) was added to the signal such to reduce the overall SNR. This was done in Matlab where additional noise was added such that the ΔSNR ranged from 0 to -30 dB. This is noted because the SNR of the original signal is unknown, thus the SNR of the signal with additional noise is also unknown. In order to obtain meaningful results it was necessary to conduct multiple noise trials. As expected, when larger amounts of noise were added to the signal, $\Delta\text{SNR} > -15$ dB, the results varied significantly dependent on the realization of the added noise for that trial. Therefore, each ΔSNR value was repeated 50 times with the accuracy results of the individual noise trials averaged.

4.2. Numerical Results and Performance Analysis

Figure 2 shows the classification accuracies for a single noise trial as a function of the ΔSNR. The results for each of the 5 stimulus frequencies are provided. Each point plotted in Figure 2 is the average of the ten 2-second segments. The mean of the 5 frequencies is also provided and for comparative purposes the mean classification accuracy using CCA is also plotted. CCA classification was computed using the methodology described in [16].

As previously noted, the results in Figure 2 are somewhat erratic at higher levels of additive noise. Figure 3 provides the average of 50 noise trials. In this case each point plotted represents the average of 500 2-second segments. Again the mean accuracy using SCA and CCA are provided.

As shown in Figure 3, the classification accuracies SCD and CCA detection methods are similar, with cyclostationary-based detection slightly outperforming CCA at higher levels of additive noise. The accuracies across all frequencies are are close to 100% when there is no additive noise. This is true for both SCD and CCA detection methods. Further, the accuracies remain above 90% until after the SNR has been reduced by 10dB. After the SNR has been reduced by 15 dB, the accuracy drops quickly below values acceptable for a BCI system, and we note that the two methods (SCD and CCA) have comparable performance when large amounts of noise have been added.

5. CONCLUSION

In this paper we studied the cyclostationary-based detection of SSVEP and presented numerical results comparing corresponding classification accuracy to that of CCA detection. The results are intended to assess the feasibility of the studied method, and show that cyclostationary-based detection can be successfully used for SSVEP detection and classification.

Further investigation should include multiple subjects as there is variability between the SSVEP characteristics across subjects. Additional studies should also consider analyzing noisy data collected with inexpensive EEG equipment rather than adding artificial noise to data collected with research grade equipment, as well as testing higher stimulus frequencies to further evaluate the SNR performance.

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