

Characterizing the SSVEP Spectrum Using a Broadband Noise Stimulus

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Abstract. Steady-State Visual Evoked Potentials (SSVEPs) are oscillating components of the EEG that are detected over the occipital cortex, having frequencies corresponding to visual stimulus frequencies. SSVEPs have been demonstrated as effective signals for rapid and reliable control of a BCI. While SSVEPs tend to be most prominent in the range of 5-40 Hz, the optimal stimulus frequencies are subject-dependent and can reside anywhere within that range. In traditional approaches the user's optimal SSVEP frequencies are determined by an exhaustive evaluation of predefined frequencies. The proposed approach aims to quickly characterize the SSVEP spectrum to identify the optimal SSVEP frequencies using a single broadband noise stimulus.

Keywords: Steady-State Visual Evoked Potentials, Spectral Analysis, EEG

1. Introduction

SSVEPs have proven to be very effective control signals for EEG-based BCIs [Cheng et al., 2002; Kelly et al., 2005; Müller-Putz et al., 2008]. In order to continue pushing the performance limits, various aspects of visual stimulus design and presentation have been examined in the context of BCI [Lee et al., 2011; Jia et al., 2011]. In spite of this sophisticated recent work, there are opportunities to improve traditional fixed-frequency SSVEP approaches. In most SSVEP-BCI designs, the subject is presented with multiple simultaneous stimuli. The optimal frequencies for fixed-frequency stimuli are highly subject-dependent and harmonic frequency relationships must also be considered [Zhu et al., 2010]. Therefore, it can be cumbersome to design an optimal BCI interface using multiple fixed-frequency stimuli.

Several recent studies have examined the use of broadband (i.e., containing equal power at all frequencies within the band) visual stimuli such as white noise [Lalor et al., 2006] and m-sequences [Bin et al., 2011]. In [Lalor et al., 2006] band-limited white noise visual stimuli were used to successfully develop a linear model of EEG visual-evoked potentials. Using the same linearity assumptions and stimulation approach, it is conceivable that stimulation with this noise can approximate the full SSVEP frequency spectrum. The proposed method aims to efficiently characterize the SSVEP spectrum to identify the optimal SSVEP frequencies using a single broadband noise stimulus.

2. Material and Methods

Data were collected from five able-bodied subjects (4M, 1F; average age 25). The subjects wore an electrode cap fixed with sixteen active electrodes (g.tec g.GAMMAsys) focused over the occipital sites (Fz, Pz, Poz, Oz, Po3, Po4, Po7, Po8, O1, O2, Oi1H, Oi2H, Poo1, Poo2, Poo3, Poo4). All locations were referenced to the left mastoid with the right ear serving as a ground. The EEG was amplified (g.tec g.USBamp) and digitized at 256 Hz. All aspects of the experiments were controlled by BCI2000. A custom stimulus presentation application was written using C++, which flashes a square with variable frequency and intensity on a monitor with a 60 Hz refresh rate. The subjects sat 60 cm away from the monitor with the flashing square occupying 7 x 7 degrees of visual angle. Eleven stimulus conditions were examined: ten frequencies where the square alternated between black and white at the sub-harmonics of 60 Hz from 5-30 Hz; and a band-limited white noise (at 30 Hz based on the monitor refresh rate) that changes each frame based on a uniform random distribution of 256 gray-scale intensities between black and white. Each condition was presented sequentially in a counterbalanced fashion for one minute, with a 30-second break between conditions. Two minutes of baseline data were also collected.

Data were analyzed on a per-channel basis. The EEG signals were first band-pass filtered between 2 and 35 Hz. For each channel and stimulus condition, the EEG power spectra for 1-second sliding data windows (using a Hamming window) and 1-sample overlap were computed using a 2048-point FFT. The power spectra for the

baseline condition were computed using the identical procedure. The Fisher Ratio (squared difference of the means over the sum of the variances) between the resulting spectra for each stimulus condition and the baseline spectra was then computed for each spectral bin as a measure of discriminability from baseline.

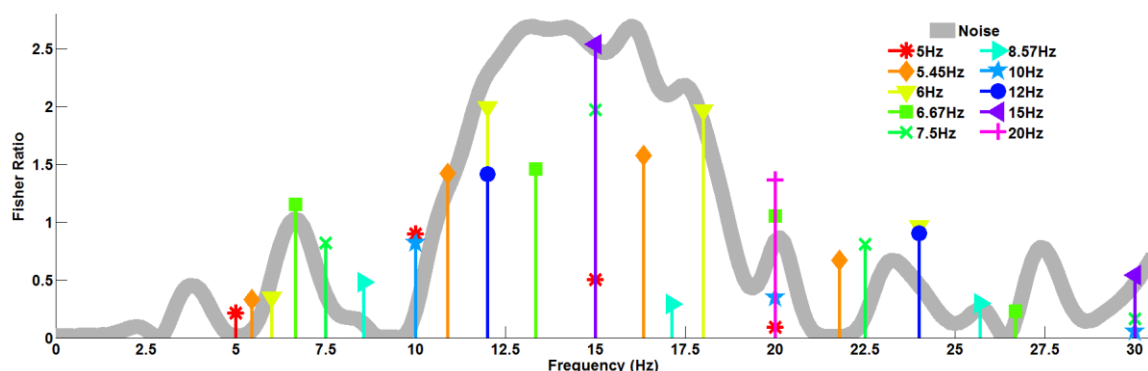


Figure 1. Results for a representative subject from channel Oz. The Fisher Ratio of the noise power spectrum and the baseline power spectrum is shown as the solid gray trace. The Fisher Ratios of the SSVEP power spectrum and the baseline power spectrum for each stimulus frequency are shown as the colored stem plots. The fundamental frequency and the subsequent three harmonics are plotted for each stimulus condition.

3. Results

Fig. 1 shows the results for a representative subject at channel Oz. The Fisher Ratios for each SSVEP stimulus condition at the fundamental frequency and the subsequent three harmonics are plotted as the colored stems. The gray trace shows the scaled Fisher Ratio for the band-limited white noise stimulus across the entire frequency spectrum. Because the objective is to identify the optimal SSVEP frequencies, the Fisher Ratio of the noise is scaled to align with the SSVEP data to better illustrate the relationship between the noise and SSVEP spectra.

4. Discussion

The Fisher Ratio of the noise stimulus spectrum closely aligns to the distribution of the Fisher Ratios for the majority of the SSVEP frequency conditions and their respective harmonics. While this method appears to give a strong indication of the optimal and undesirable SSVEP frequencies, it does not provide a complete and definitive characterization in its current form. This is due to two primary factors: (1) the stimulus frequencies are highly limited by the monitor's refresh rate and (2) the relationship between the programmed stimulus sequence and the EEG is clearly not linear. Future studies will extend these results by presenting continuous stimuli on an LED display that is not limited by a refresh rate, and to better characterize the nonlinear relationship between the stimulus sequences and the EEG.

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